Sectoral Unemployment during the COVID-19 Recession in the United States: A VAR Analysis

Utilizing historic business cycle data to model industry specific recessionary paths and discern high risk sectors.

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Abstract:

This paper examines the interaction between unemployment, economic activity factors and inflation at a sectoral level. The intention is to ascertain unemployment rate forecasts for each Super-sector of the United States economy during the first year of the COVID-19 pandemic, concluding on its intricacies and sectoral deviations. Out of the 12 Super-sector models, only the Agricultural sector provided statistically accurate forecast estimates. Further statistical analysis is therefore applied to identify Super-sectors at high risk of long-term recessionary exposure. The Mining, quarrying and oil and gas extraction and Leisure and Hospitality Super-sectors are deemed to be at the greatest risk of sustained sectoral unemployment. The onset of the COVID-19 outbreak has induced recessionary economic conditions globally due to the disruptive nature of pandemic conditions and mitigatory government responses. It is likely that recessions caused by pandemics are fundamentally unique and will result in sectorally unequal outcomes. VAR techniques will be applied to a timeseries dataset covering 12 US Super-sectors over the period 2000-2020. Research results provide evidence that the COVID-19 Recession does not follow the unemployment transmission pattern of prior recessionary events.

1. Introduction:

SARS-CoV-2 is the strain of novel coronavirus which is responsible for the ongoing COVID-19 pandemic and ensuing economic recession. The first reported human cases of COVID-19 were from within Wuhan City, China in December of 2019 (WHO, 2020). In part due to the complexity of the strain's mechanisms for transferal and asymptomatic infection, an exponential global decline towards pandemic status followed its discovery within the first quarter of 2020 (Pitlik, 2020). The first internally contracted positive case of the virus confirmed in the United States was reported on the 26th of February 2020, heralding the commencement of a socio-economic crisis which would pose an unprecedented challenge to the nation's employment structure and workplace practices. This crisis manifested as more than simply a public health emergency. Efforts to limit transmission of the virus by way of lockdown restrictions have formed an economic vacuum, generating immense shocks to both supply and demand on an international scale. The aims of this paper are two-fold. It intends to identify the nuances of a recession driven by a global pandemic, whilst also delineating the economic consequences of such a recession upon unemployment within industries vastly differing in terms of their exposure to pandemic effects. Econometrically, it presents a Vector Autoregressive (VAR) model, created in RStudio, (RStudio

Team, 2021) comprising of industry-by-industry unemployment forecasts of the first twelve months of the pandemic. Accuracy is determined by comparing forecast estimates to recorded unemployment data from across the 12 major US employment Super-sectors as identified by the US Bureau of Labor Statistics (BLS) (BLS[A], 2021). By analyzing the predictive accuracy of traditional forecasting methods when applied to this recession, one may be granted some insight into the necessary direction and magnitude of future recovery policies. Furthermore, the industry-by-industry approach should highlight which individual sectors have been disproportionately affected by the onset of the COVID-19 pandemic, affording conclusions on the nature of suitably directed responses and innovations to avoid sectoral shrinkage.

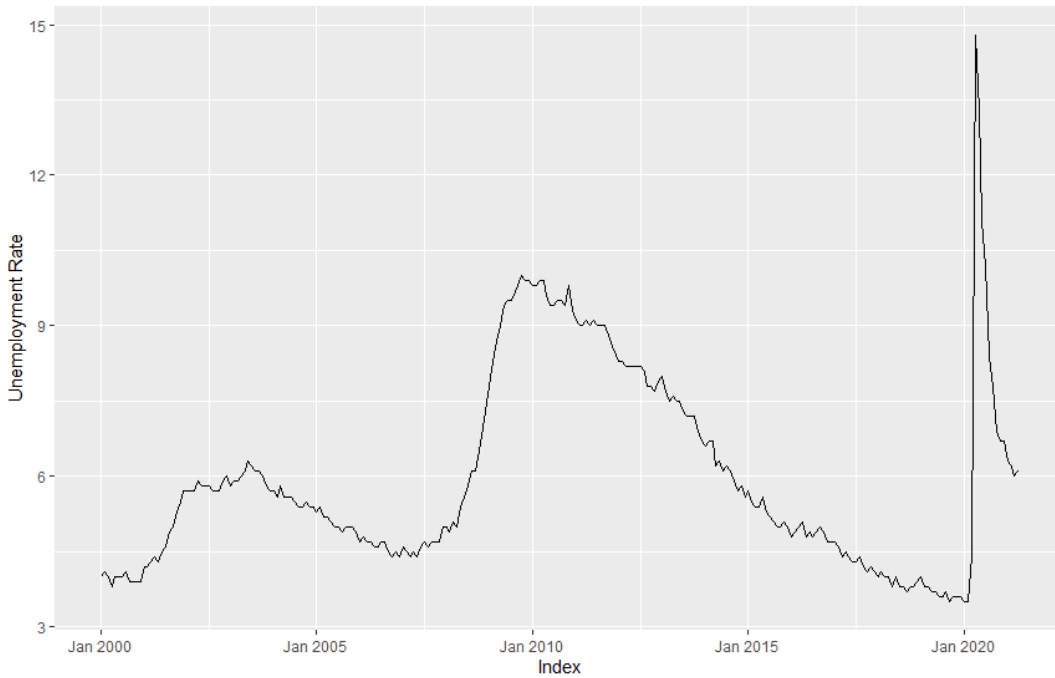
The US poses an ideal focal point for a study such as this, given the profound impact the outbreak has had on the nation. As of March 2021, 25.29% of all worldwide COVID-19 cases were distributed amongst the United States, despite accounting for only 4.25% of the total global population (Statistica [A], 2021). Furthermore, COVID-19 containment policy was uniquely dictated at a predominantly State level in the US. Irrespective of the core political motivations for this delegatory policy, enacted by then sitting President Donald Trump, in the context of this study, it grants a great deal of insight into how differing pandemic policies interacted with employment within specific industries at a regional level. This will assist in policy analysis from a labor market perspective. An additional motivating factor for this US centric analysis is the availability of detailed historic and even state-specific sectoral data, provided by the BLS. The depth and breadth of this accessible data far exceeds that of any other OECD nation over the period, affording analysis at even a sub-sectoral level.

Regarding the statistical implications of the pandemic, it is irrefutable that the SARS-CoV-2 virus is responsible for increased mortality rates globally. As of March 2021, more than 500,000 individuals have perished due to confirmed or presumed COVID-19 in the US alone. At the time of writing, this figure is closing on 2,700,000 worldwide deaths (Statistica [B], 2021). From a humanitarian perspective, this is a disastrously high death-toll, with increased mortality contributing to both demand and supply side shocks. However, economically, it is not a contraction which equates to the loss of global output and employment witnessed since Q1 of 2020. In fact, six months into the pandemic, roughly 80% of US deaths had occurred among people aged 65 or above, most of whom were no longer part of the recorded workforce (Quast et. al, 2020). Yet, in 2020 the US reported a 3.5% contraction of its GDP as unemployment rose to 23.1 million individuals at its peak in April (McCormick, 20201), evidence that there are more nuanced inferences to be made during a pandemic induced recession. The low mortality rate of COVID-19 may be somewhat indicative of this, as only 1.8% of cases in the US have been fatal (Johns Hopkins CRC, 2021), but due to the infectious and potentially debilitating nature of the virus, the 29 million cases have resulted in lost working hours, another productivity and labor supply shock. Equally, the pandemic has brought about a great deal of uncertainty amongst the populace, dampening the confidence of key economic actors. In general, these economic burdens will impact the economy unilaterally. This paper is more so motivated by a desire to analyze the pandemic's sectorally divergent implications. Beyond lost output and demand as a result of death and illness, the truly insidious nature of this pandemic is witnessed in how it has been the governmentally endorsed infection prevention measures which have most negatively impaired economic performance and may have inflicted the greatest wounds upon the economy in the long run. Lockdown measures such as Stay at Home Orders, Out-of-State Travel restrictions and close operating proximity business closures enacted between March and April of 2020, across the majority of states in the US (at differing intensities and time frames) have negatively influenced aggregate demand and supply across the nation. They have led to falling consumer demand as a result of layoffs and reduced work hours as well as disrupting supply by way of business closures and effectively immobilizing the workforce. In the US alone, 9.2% of working hours were lost in 2020 when compared to quarter 4 of 2019, equating to 13,000,000 lost jobs nationally (ILO Monitor, 2020).

This paper does not intend to sermonize regarding the potential tradeoff between maintaining life and maintaining livelihoods. The necessity of such life-preserving policies is unquestionable when considering the alternative, being overwhelmed health service providers alongside a greater virus incidence and mortality rate. A November 2020 study indicated that non-pharmaceutical interventions are necessary in slowing down the spread of the virus, with closures and lockdowns ranking amongst the most effective methods at a government's disposal (Haug et. al, 2020.) The gathering consensus is that whilst there may have been less intrusive policies which could have been leveraged to mitigate these effects, more so than response deficiency, it was a politically motivated ambivalence to pandemic preparation which led to these profoundly damaging socio-economic outcomes (Mellish et.al, 2020). Irrespective of causation and fault, these restrictive policies were implemented, operating counter to the neoliberal, free market economics which has typified US economic policy in the 21st century. Undoubtedly, they had an immediate cross-industry impact, with businesses adopting remote technologies to facilitate their continued operations. However, these restrictive policies were not universally introduced, nor equivalently impactful across economic sectors. Certain industries lacked the infrastructure to support remote employment or socially distanced consumption, whilst others required a consumer's physical presence to provide their service. These more 'tactile' industries, which are enabled by human proximity, were interfered with disproportionately by lockdown measures. This has created a sectoral disparity which, whilst notable throughout the initial stage of the pandemic, will likely become more economically significant as the global economy continues to recover. The fear being that certain industries have suffered such significant financial losses over the closure period that they will be unable to recover to their pre-pandemic state, or a greater appreciation for microbial infection control will prevent their continued operation in a post-COVID-19 world. Should this occur, there is a danger that the US will experience a K-Shaped Recovery, wherein the diverging fortunes of COVID-19 resistant industries will be juxtaposed by those most adversely impacted. This holds wider implications for inequality and unemployment nationwide. With a recovery divergence already forming within the United States the purpose of this paper is further elucidated (ILO Monitor, 2020).

As has been observed, a pandemic induced recession will interact with differing industries in an inequitable and unpredictable fashion given the transmission mechanisms of the virus. Historically, one would anticipate the emerging unemployment in one industry to fill spare capacity within another transferable industry, much as was witnessed throughout Thatcherite Britain's sectoral transferal towards financial services in the 1980's. However, considering the additional economy-wide pressure induced by a more potentially prolonged and widespread recession, employment availability mismatch could potentially stunt that recovery and lead to greater structural unemployment in the long run (BoE, 20201). As was identified by Loungani, Rogerson, and Sonn (Loungani et.al, 1989), cross-industry labor movement is usually met with longer unemployment spells when compared to intra-industry reallocation. Thus, it is also important to consider whether the initial extreme employment figures witnessed during April 2020 can be viewed as simply the result of a 'Black Swan Event' or, if they highlight a more inherent problem with close operating proximity industries. Following a change in legislative attitudes towards pandemic proofing, coupled with shifting public opinion regarding teleworking and long-range consumerism could such unemployment have been prevented? Furthermore, could the aftershocks of such an event have the potential to enter the global economy into a more sustained recession with cross-sectoral ramifications?

Figure 1: Seasonally adjusted total monthly US unemployment rate



Source: Data from FRED (FRED [C], 2021)

The most reliable method to approach questions such as these is to compare the COVID-19 Recession's impact on unemployment to prior recessions with structural similarities. Given the apparent early-stage uptake and efficacy of COVID 19 vaccination in the US (Ritchie et. al, 2021), there is hope that this may turn into a more economically and less medically variant issue. Thus, there is value in retroactive comparison, which this paper will apply to inform conclusive policy recommendations. There is a natural inclination to compare this 2020 recession to the Great Recession commencing in 2007, given the similarly inequitable way in which industries were inevitably affected by the fallout of the Subprime Mortgage housing bubble. However, this was an extended decline into recession, with unemployment in most industries being predictably lagged as foreclosures took place and financial institutions were liquidated. The initial lockdown period of the COVID-19 Recession had a comparatively deep and instantaneous effect on most industries as can be seen in the aggregate unemployment chart Figure 1. As such, the two recessions appear very different in terms of timing and scale. In many ways the current recession is more so akin to the 1945 recession, wherein demobilization from the end of World War 2 created an almost instantaneous shortfall in US GDP and employment. Unfortunately, sectorally specified data from that era is exceptionally limited. Yet, if one looks beyond the initial lockdown period, after the artificial restriction of employment began to subside, it appears that recognized long-lasting negative shocks, driven by uncertainty take over. There is an initially robust recovery across most industries as employment demand is filled by those temporarily unemployed which trails off into a less volatile economic downturn. In fact, the state of US unemployment in 2021 appears to mimic that of the post Great Recession recovery, with many industries still exhibiting unemployment rates within 20% of their 2007-2011 peaks. This is a somewhat worrying premonition if one recollects that the Great Recession recovery was gradual, relative to its depth. Policies undertaken by the Obama Administration to augment this recovery exemplified Keynesian budget deficit spending and a desire for economic and financial re-engineering (Boskin, 2020). Early signs from the Biden Administration indicate that a similar approach is being considered (Joe Biden for President: Official Campaign Website, 2021), whilst publicly held Federal Debt has continued to grow as a percentage of GDP to above 100% in the wake of the COVID-19 crisis. Coupled with a genuine and warranted demand for global structural change and pandemic proofing, it is likely that these systemic overhauls will interfere with the rate of recovery. This paper intends to leverage these observations when concluding on policy recommendations. Unfortunately, current economic conditions are too closely tied to the trajectory of the pandemic to boldly assume economic patterns will play out exactly as they did in the past (Boskin, 2020). COVID crisis analysis remains a highly dynamic field of study as mutations and virus variants continue to change the landscape of scientific research in ways that even vaccination may not prevent. From an economic perspective, this is pertinent to the future of policy making. The ever-evolving situation makes static prediction troublesome for economists, not only from the perspective of a potential further health crisis directly impeding a recovery, but also in terms of how consumer and business confidence will manifest when the public is greeted with this asymmetric and often inconsistent information. As such, this paper's model does not aim to forecast into the future, instead it intends to ascertain the predictability of the COVID-19 recession using prior recession data to better grasp the scenario and scope for response.

Methodologically, this study uses a core multivariate VAR structure with 5 timeseries variables to model the unemployment rate of each sector in the US. This structure is replicated across 12 separate models, each varying the Super-sector of unemployment that is to be forecast. Additionally, residual unemployment, or the total national unemployment occurring outside of each focal industry, will vary slightly between each model. This residual is an important indicator as one would expect the wider unemployment situation to have some bearing on that of a specific industry. The extent of this relationship may assist in determining how interdependent a Super-sector's unemployment rate is. The other variables are standardized across all 12 models, being identifiable and measurable potential transmission mechanisms for pandemic induced supply and demand shocks upon the unemployment rate. Historically, these are variables which respond to an initial shock, signaling the future movement of the often-lagged unemployment rate. Economic activity, as measured by Gross Domestic Product (GDP), has a well-documented and observable negative relationship with unemployment rates as first formalized as Okun's Law (Okun, 1963). A change in GDP tends to capture some shift in aggregate demand or supply. Total industrial productive output will likely display a similar relationship to GDP, the magnitude of which is seemingly related to the supply chain dependency of an industry. The inflation rate has an indirect but equally relevant relationship with unemployment. One would anticipate high inflation rates to signal low unemployment, as it is indicative of the rising wage prices which occur as high employer demand is met with an increasingly low labor supply. This relationship is portrayed by the Phillips curve, an indicator that has been weakening in its reliability of late (Ng et.al, 2018). Within this overarching framework, the intention is to forecast all 12 of the Supersector's unemployment rates over a 12-month period starting from March 2020, the first month of the COVID-19 Recession. These industry specific estimates can then be compared to their actual unemployment outcome data to calculate forecasting errors and ascertain the reliability of the model during a deep recession such as this.

This study aims to be replicable and non-nation specific in its conclusions and recommendations. The COVID-19 pandemic is still very much a globally distributive phenomenon that has presented extreme challenges on a broad scale. As has been stressed by other academic authors, globally, humanity was sorely unprepared for the outbreak of a pandemic such as this. Leading up to 2020, societally and institutionally, there was an economic overreliance on high proximity activities alongside what appears to have been an underlying educational asymmetry regarding microbial transmission of viral diseases (Pitlik, 2020). Coupled with limited national and international discourse amongst key governmental decision makers, scientists and economists, initial responses to the crisis were sporadic, inconsistent, and met with public dissent in some cases. This study does not aim to refute any of these likely explanations for the severity of the outbreak. Its focus is upon analysis of the continued economic recession preceded by the pandemic. Beyond this, it will attempt to clarify the predictive statements made in the April 2020 edition of the International Labor Organization Monitor (ILO) (ILO Monitor, 2020), regarding sectors at high-risk of disruption and their applicability to the US situation. These sub-sectors fall into the definable BLS Super-sectors of Wholesale and Retail trade, Professional and Business services, Leisure and Hospitality services, Financial activities and Other Service provision.

Despite being successful in forecasting all sectoral unemployment rates prior to the COVID-19 Recession, 11 of the 12 models were shown to be unreliable when estimating the COVID-19 period. Only the model for Agricultural Unemployment returned a Mean Absolute Scaled Error (MASE) which was less than 1 and thus better than the naïve model. This suggests that the model was misspecified for other sectors during the COVID-19 Recession and that it is unlikely that unemployment in agricultural related industries followed a recessionary pattern. Given that this model intentionally includes data from the Great Recession to make this forecast, it is inferable that the current recession is unique both in terms of the magnitude and rate of the unemployment rise and recovery. However, the reliability of this model is apparent when forecasting industry specific unemployment levels during non-recessionary periods and may still be of some worth in studying industry quirks, offering insights into industry targeted impulse response functions for the interacted variables. Given the possibility this was purely a 'Black Swan Event', these identifiable impulse relationships may be of use in estimating the flow of the recovery and targeting industry specific policies. As anticipated by the ILO, the Leisure and Hospitality service sector has been majorly affected by the pandemic, yet the Transport and Mining and Extraction sectors have also suffered intense unemployment rate declines from February 2020 to 2021. Furthermore, there are additional sectors of employment, such as those who offer interpersonal services (the 'Other Services' sector) which have also yet to show an equiponderate recovery when compared to their post millennium averages. This paper has found that early pandemic predictions failed to fully comprehend the complexities of the sectoral strengths and deficiencies which have exemplified the US unemployment situation over the past year. As governments proceed with the implementation of policies to augment recovery it is crucial that they do so with extreme trepidation. Most industries appear to be no better off than they were during the early 2010's despite exceptionally high growth initial figures emanating from reemployment uptake. Very little of this recovery appears to have been founded in a change of economic conditions or sentiment and the wider economy runs the risk of entering another decade of half-speed growth akin to the relatively stagnant 8 years following the Great Recession (Boskin, 2020). If a balance is not struck between regulatory measures to prevent a future pandemic being so destructive, whilst supporting those highly exposed sectors from collapse, a double dip-recession is undoubtedly a possibility. Either because of a failing sector, or a health crisis relapse.

The remainder of this paper is structured as follows: in Section 2 the state of prior knowledge regarding VAR forecasting of unemployment rates, sectoral unemployment factors and pandemic specific recessions is reviewed. Section 3 presents and offers visualizations of the data utilized by this study. Section 4 discusses the methodology and statistical rigor applied to this data. In Section 5 forecasting and inter-variable relationship results are presented. Section 6 will discuss these results, offering explanations and policy recommendations in light of them. Finally, Section 7 provides concluding remarks on the findings of this study.

2. Literature Review:

Economists hold an enduring interest in the interconnectivity of macroeconomic variables. The sustained study of these relationships underpins economic policy with regards to key economic objectives. Since 1962, when Okun's seminal work identified the statistical negative correlation between GDP growth and unemployment (Okun, 1963), the relationship has been rigorously investigated and applied within numerous forecasting models (Ball et.al, 2015). The reliability of the relationship dictated by Okun's law as a forecasting tool has been vigorously researched, with Knotek's 2007 study (Knotek II, 2007) finding it sufficiently useful when business cycle instability is accounted for, a conclusion echoed by Furceri et. al (2019). This robustness is key when applying it within the framework of the models in this paper.

Expanding upon general predictive studies, the nature of such interactions during periods of great uncertainty in the wake of acute financial shocks is exceptionally pertinent when applying past literature to the modern pandemic situation. Caldara et. al's 2016 study into the macroeconomic impact of financial and uncertainty shocks presents the disruptive interaction between the two symptoms of recession from the perspective of the economic fluctuations experienced during the Great Recession – a pivotal point of comparison in the 21st century. Such disruption is likely to be further aggravated by the unique fear associated with infection apparent during pandemic situations. The modern macroeconomic effects of such an event have previously been estimated within the hypothetical scope of a Europe pandemic. Jonung and Roeger's study (2006) is astute in its consideration for severely exposed economic sectors but is disadvantaged by the innate difficulty of extrapolating data from the Spanish influenza in 1918-19 for use in a predictive estimate within a theoretical modern scenario. Given the changes that have occurred in global interconnectivity and medical technology, it is unsurprising that the posited situation is not representative of the ongoing pandemic. Predominantly, it was the duration of a potential pandemic which was vastly underestimated, resulting in the economic implications being generally misspecified. With the benefit of modern pandemic data, it is possible to measure whether these macroeconomic implications are within the scope of a major recession as was predicted in 2006.

Should that not be the case, this paper's investigation into sectoral disadvantage will be all the more pertinent.

There has also been a tremendous appetite for economic study of the unique conditions presented by the COVID-19 pandemic. Undoubtedly, there is a growing necessity to investigate these unprecedented peacetime macroeconomic variations, both to calculate appropriate response policies and mitigate future occurrences. As a dynamically evolving field of study, there is additional need for overlapping topic research. The 'Literature Review of the Economics of Covid-19' offers an introduction to the nuances of situation during initial prevention measures (Brodeur et.al, 2020). It collates the literature which has emerged within the initial 6 months of the outbreak, offering insight into the immediately observable socio-economic consequences, in a generalized and accessible format. Gallant et. al (2020) approached COVID-19's temporary unemployment situation with a search-and-matching unemployment model, which concludes, surprisingly, that professional unemployment forecasts are underestimating the speed of recovery they would anticipate from the US labor market. An opposing viewpoint is presented in Bianchi et. al's (2021) investigation into the COVID-19 unemployment shock's long-term impact upon life expectancy. It provides a contradictory long-term outlook; illuminating the potentially damning trajectory this crisis may take over the next two decades without sufficiently targeted government maneuvers. Likely a conclusion which places greater emphasis on the unprecedented magnitude of the initial unemployment shock. Gallant et. al argue that job discovery rates have not reduced as substantially as seen in past recessions and this divergence from the standard dynamics of a recession will result in a rapid recovery within the next 18 months. However, they fail to fully account for the structural vulnerability of employee retention schemes such as the Paycheck Protection Programme and Employee Retention Tax Credit scheme (OECD, 2020). Once they are withdrawn, if there isn't sufficiently robust aggregate demand and pandemic-proof working conditions in place, job availability will likely recede and recall rates plummet. It is not so much that this paper is inclined to disagree with their findings. More so, that industries which appear vulnerable to sustained low demand or unfeasible operating conditions must be identified and supported in order for these optimistic unemployment estimates to come to fruition. The pivotal difference between the two paper's conclusions likely comes from how they value the predictive relevance of historical recessions and pandemics. Where Gallant et. al's paper is exceptionally astute, is in calling into question the validity of past recessions to guide future action, a conclusion which this paper intends to analyze further.

There have been far fewer previous studies which have specifically investigated how individual sectors of the economy respond to macroeconomic shocks. Bäurle and Steiner (2015) developed a model to capture how independent shocks such as changing interest rates or exchange rates would heterogeneously affect each sector. This is evidence that a sectoral approach is of merit when considering the shocks induced by the COVID-19 pandemic. There are also several papers which study the relationship between sectoral shock and unemployment specifically. Lilien's 1982 publication denotes sectoral demand driven unemployment as predominantly cyclical, but responsible for aggregate unemployment fluctuations (Lilien, 1982). Riordan and Staiger (1993) go beyond this, finding that prospective employer information asymmetry makes finding reemployment, within a different sector, difficult for many. They discuss the likelihood that sectoral unemployment will manifest as structural in nature. This conclusion is exceptionally pertinent to the COVID-19 situation and the case made for the provision of "adjustment assistance to workers leaving the injured sector" (Riordan and Staiger, 1993) will be echoed by this paper. Dissenting suggestions that "gross intersectoral flows through unemployment are always positive," (Pilossoph, 2012) have not accounted for an unprecedented situation such as this and are reliant on *a priori* assumptions. Furthermore, in most cases, these shocks are considered as sectorally isolated, not as universal shocks which have simply impacted certain industries more than others. Worker movement into a relatively more productive sector is unlikely to take place when that sector is facing a similar, if not as acute, crisis.

Unsurprisingly, with the asymmetric effects of the COVID-19 crisis at the forefront of discussion, there has been an increase in sectorally focused publications. The Office for National Statistics in the UK published an article identifying the widening sectoral growth disparity (ONS, 2021). This article notes the industries which actually recorded a growth in sales during the period, potentially granting some insight into where ailing sectors should focus their recovery strategies. Del Rio-Chanona et.al (2020.) provide key classifying information with regards to the sectors which are well suited towards remote functionality. They also denote the nature of the shock likely experienced by each major sector, granting insight into how their eventual recovery troubles will manifest, as well as what form of policy may best aid their recovery. One worrying conclusion is that low-wage occupations are more vulnerable to such shocks, a further concern when considering the potential for a sectorally driven widening of the inequality gap. Sectoral discrepancies are clearly pivotal factors when judging the depth of the COVID-19 recession and universality of recovery. However, thus far, little has been done to model and predict the extent to which pandemic exposed industries will capitulate in terms of labor market retention. There has also been limited consideration for industries that will simply cease to function under particularly egregious environmental conditions, which could be disastrous not only for those employed and trained in those areas, but also from a cultural perspective.

Regarding the application of forecasting methods to the economic conditions of the COVID-19 crisis, Foroni et. al. (2020) utilizes sophisticated augmented mixed frequency models to ascertain how best to capture the irregularities of the crisis period effects. However, whilst these forecasting adjustments may lead to smaller forecast errors across the unemployment variables, the intention of this paper is not to provide the most accurate crisis level forecasts. Instead, it is targeted at identifying what makes this recession unique and which channels of employment these unpredictable fluctuations effect the most. Following a similar approach and using the Great Recession as the basis to estimate the model, as produced the best results for Foroni et. al., would be ill advised in this study, as the sectoral deviations from two uniquely caused recessions would be muddied. As such, to maintain the clarity of each Super-sector's relationship with the interacting variables, a simple VAR model was chosen. The Vector Autoregressive model was posited by Christopher Sims as an alternative system with which to model and forecast the dynamic, causal relationships between macroeconomic variables by treating them as endogenous (Sims, 1980). This model has been revised and re-specified over the ensuing decades, but its core intention to apply univariate autoregression across a vector of macro-variables has been retained. Kishor and Koenig (2012) find that applying a finite lag to government estimates produces a more competitive forecast when data is subject to revision, likely essential at such a volatile situation as the COVID-19 pandemic, wherein data revisions may entirely alter the essence of a government publication.

Loungani and Trehan (1997) used a similar five variable VAR model to measure what proportion of a change to unemployment can be attributed to a sectorally isolated shock as opposed to simply an aggregate shock. It made use of an innovative conceptual link between the health of an industry and that industry's stock price index relative the growth rate of the S&P500. The concept, that stock market price dispersion can predict the long-term significance of a shock, is grounded in the idea that stock prices reflect the perceived value of an industry in real time, whereas employment is understandably lagged. This method is far less applicable to the modern trading environment or to the current situation. Unemployment seems to be moving independently of stock prices and the market itself appears to no longer be beholden to fundamentals. Speculative recovery bubbles are forming around industries that this paper will show are unlikely worthy of the faith being placed in them, driven by the wealthiest in the country who own over 50% of total equity-market assets (Roubini, 2021). With the stock market no longer reflecting the overall economic health of an industry, this method cannot be leveraged here. However, Loungani and Trehan's research conclusion, that sectoral shocks tend to explain a significant proportion of long-duration unemployment, was significant in inspiring discussion throughout this paper. When applying a VAR model to the COVID-19 situation or any other pandemic, the literature is still relatively limited. Initial models predominantly aimed to forecast the depth and breadth of COVID-19 incidence or its mortality rates (see: Hafner, 2020 and Khan et.al, 2020). The emerging macroeconomic literature has tended towards predicting outcomes for major macroeconomic variables on a considerably more local study area (see: Gharehgozli et.al, 2020 and Djurovic et.al, 2020). This paper intends to be the first to use a VAR framework to consider COVID-19 era unemployment on an industry-by-industry basis. In doing so, exploring how the uneven nuance of a pandemic driven recession in the modern, interconnected world may inadvertently forge the ideal conditions to profoundly grow national and international inequality.

3. Data Introduction:

3.1 Data

Regarding the acquisition and decision-making processes behind the data utilized in this study; all variables were chosen either due to having a theoretically founded causal relationship with aggregate unemployment, or an intuitive relationship with industry specific unemployment. Sectorally divided employment is an easily understood concept, yet unemployment is an unambiguous classification that is representative of all jobless employment-seekers. As such, the recording of industrial or sector specific unemployment is based on the last held job of the unemployed individual. It captures the shifting health of an industry more succinctly, accounting for sectoral employment trends irrespective of the growth or shrinkage of an industry or wider economy thus making it more suitable for cross-industry comparison especially during a period of recession. Within this study, twelve core industrial classes of employment were chosen to represent aggregate unemployment in a sectorized fashion. The twelve were decided upon through the utilization of the Bureau for Labor Statistics' own classification system, identified as core Super-sectors, reflecting census data from the census industry classification system in the Current Population Survey. Retroactively acquired sub-sector data may be leveraged to further understand the root-cause of a noteworthy COVID-19 resistant or affected industry. These classifications, derived from the North American Industry Classification System (NAICS) are as follows:

1) Mining, quarrying, and oil and gas extraction 2) Construction 3) Manufacturing 4) Wholesale and retail trade 5) Transportation and utilities 6) Information 7) Financial activities 8) Professional and business services 9) Education and health services 10) Leisure and hospitality 11) Other services 12) Agriculture and related private wage and salary workers.

This data was sourced from the BLS historical employment household data series, A-14. Unemployed persons by industry and class of worker (BLS [A], 2021). Operating under the decentralized Federal Statistical System of the US, the BLS is an agency concerned with collecting and processing statistical data within the field of labor economics with impartiality (BLS [C], 2021). The Super-sector level classifications have remained the same since the Current Employment Statistics (CES) program implemented a full conversion from the Standard Industrial Classification (SIC) system to NAICS in 2003, despite three minor industry classification updates, the latest of which taking place in 2018 (BLS [B], 2021). Data included from prior to 2003 was taken using an initial 1997 NAICS classification and does not require adjustment. Unfortunately, SIC data requires vastly transformative reconstruction for modern comparison purposes as industries such as Leisure and Hospitality were previously placed within overlapping current classifications. This limits the data range of this study to between January 2000 and February 2021, including just one global recessionary period. Furthermore, this data does not account for those unemployed without a classifiable sector, such as individuals without prior experience working. This data may be essential for another exceptionally important avenue of COVID-19 study, such as one analyzing youth unemployment or effects of hysteresis. However, it is not a necessary inclusion within the framework of industry specific research that is not targeted at capturing unemployment in its entirety.

Residual unemployment figures were also calculated, deductively, from this same data source, using unemployment averages across the 11 other industries excluded from the sectoral unemployment component of each individual model. As with all other data in this study, these figures are observed at a monthly frequency and have not been seasonally adjusted prior to entering the model.

Inflation is traditionally proxied by the Consumer Price Index (CPI), a measure which captures the average change in price of a basket of market goods and services over time. Specified within this study is a US city average collated by the BLS based on urban consumer data across all basket items. Given that inflation is, on average, historically positive in order to avoid data with a distinct positive trend, this study will include the percentage change in CPI relative to the prior period. This data is accessible from the Federal Reserve Economic Database (FRED), a time series provision and visualization tool working alongside US statistical agencies such as the BLS. Specifically, it is drawn from the 'Consumer Price Index for All Urban Consumers: All Items in U.S. City Average' publication (FRED [A], 2021). Similarly, the Industrial Output variable is drawn from the FRED's 'Industrial Production: Total Index' publication (FRED [B], 2021). As before, monthly perchance change in production is the measured statistic. This data is originally sourced from the Board of Governors of the Federal Reserve System's statistical release regarding industrial production and capacity utilization, thus it is a central bank economic report (Federal reserve, 2021). Finally, GDP is a statistical proxy for economic output and activity. Monthly change in GDP is formulated using a US Monthly GDP Index aggregated by IHS Markit, an American-British statistical information provider and trusted analytical source. This index is derived from much of the same source data used by the US Bureau of Economic Analysis to conduct their quarterly GDP measurements, but on a monthly basis. A raw monthly index is initially created and reconciled with government issued quarterly data through the use of a monthly residual (IHS Markit, 2021). This grants the intra-quarter data necessary to avoid the use of a mixed data frequency VAR method. Table 1 details the variable summary statistics for Model 1: Agricultural and related private wage and salary worker unemployment.

	Number of obs	Mean	Standard deviation	Median	Min	Max
Agricultural Unemployment rate	242	9.97	3.82	9.50	2.40	21.30
GDP percentage change	242	0.17	0.54	0.21	-1.79	1.71
Inflation Rate	242	0.18	0.37	0.18	-1.92	1.22
Industrial Output	242	0.08	1.79	-0.09	-5.00	4.86
Residual Unemployment rate	242	5.53	1.84	4.99	2.94	10.66

Table 1: Descriptive statistics

3.2 Data Visualization

All further models differ only in terms of sector specific unemployment rate and residual unemployment rate. The extent of this variation is first dependent on the natural rate of unemployment experienced by an industry. It tends to be the case that industries with more educationally rigorous entry requirements (financial services, education and healthcare services) tend to operate at lower average rates of unemployment than sectors that require less specialization, predicatively unintrusive variability in this study. Pivotally however, inter-sector statistical variation also depends on how an industry was affected by recessionary events such as the dot-com bubble or Great Recession. Conceptually, given the key similarities between the COVID-19 Recession and the Great Recession, an industry's prior unemployment reaction to the shocks of 2008-09 should be reflected in predictive data from February 2020 onwards, unless the industry has structurally undergone change in the intervening period. Unfortunately, initial recessionary data would suggest this assumption is founded upon a somewhat long-term aggregate outlook, which doesn't place enough importance on recessionary causation factors. For instance, whilst the two global recessions may share patterns of aggregate demand shortfall stemming from supply shortages and rampant uncertainly, the Great Recession was financially driven, with financial and construction jobs suffering the greatest losses due to their intrinsic relationship with the industries overheating the economy. Thus, this study falls short at capturing initial recessionary affects and specific recessionary nuances meaning, if the COVID-19 Recession is sizably unique from a prospective employment standpoint, as predicted, forecasts may be negatively impacted.

Figure 2: Historic year-on-year trends for key variables (Construction Model)

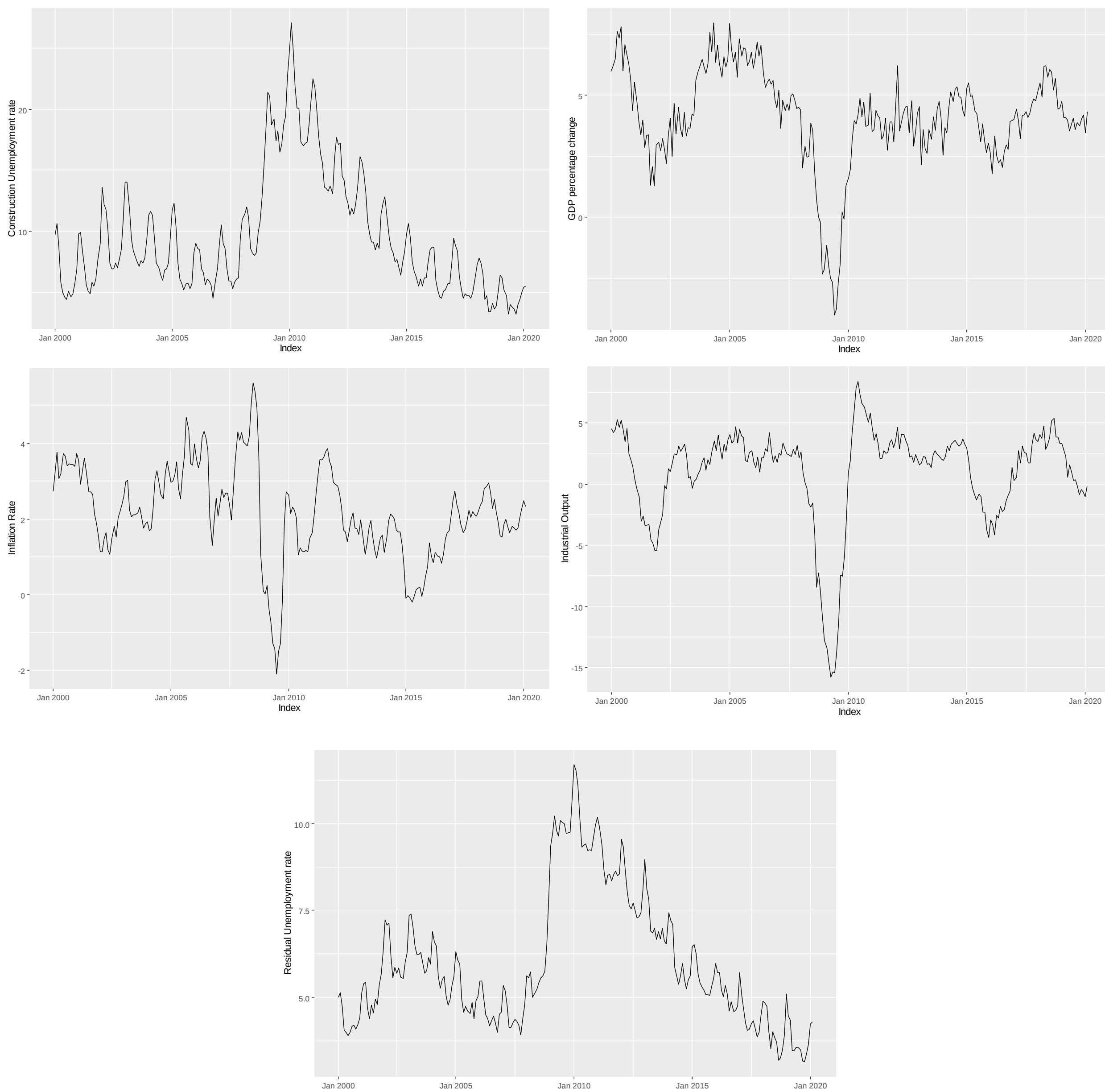
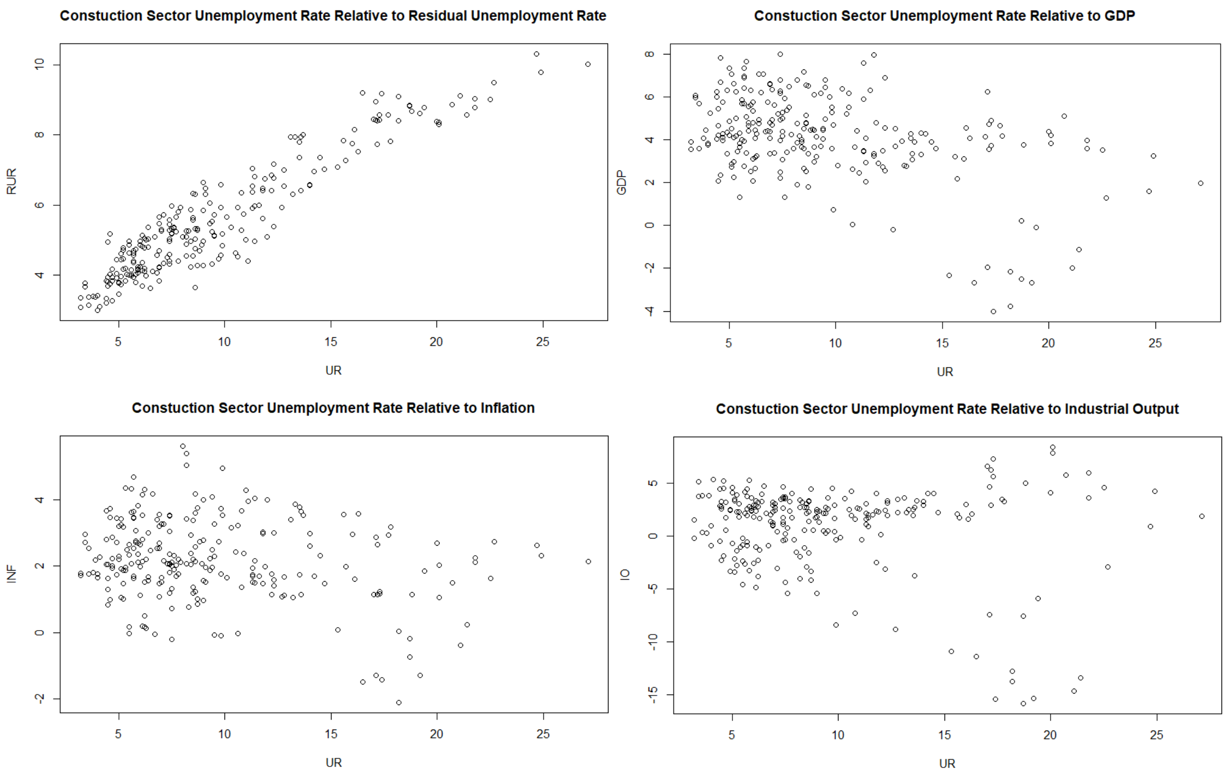


Figure 2, comprising of the previous line charts, displays the trends of Industrial Production, Inflation Rate, Gross Domestic Product as well as Unemployment rates in the Construction Industry and eleven Residual Industries across a 20-year period starting in January 2000 and ending in February 2020, one month prior to the onset of the COVID-19 Recession. For the sake of ease of data visualization, the IO, INF and GDP charts are displayed here in their non-adjusted year-on-year percentage change format and the Construction Industry was chosen to visualize an industry highly exposed to the 2008 Great Recession. The seasonal component of each should be visually apparent. There are three periods of note shared across the 5 graphs. Commencing March 2001, the early 2000's Recession. Commencing December 2007, the Great Recession. Thirdly, key variable levels in the months prior to the 2020 COVID-19 Recession. The two recessionary events both coincide with sizeable decreases in GDP, Industrial Output and Inflation rates, which are followed by greater seasonal unemployment highs and lows within both the Construction Industry and composite industries excluding construction. Even when seasonally adjusted, it appears that recessionary affects reach the labor market at a slower rate than other test variables, affirmation that there exists a generally lagged relationship. It is worth noting that, whilst not a recession of the same magnitude, unemployment returned to pre-recession lows multiple seasonal cycles faster after the 2001 Recession than following the Great Recession. This observation may have some bearing upon COVID-19 policy recommendations, especially giving the differing constraints faced by policy setters in 2021 when compared to 2008. Turning attention to the months leading up to the COVID-19 outbreak, it is worthy of mention that many industries were witnessing historically low unemployment rates in the US. This was the case for the Construction Industry in 2019 and the rising rates heading into 2020 are attributable predominantly to seasonal employment trends. So, could it be argued that the US economy was primed for a recession irrespective of the nature of its eventual cause? Adjusted employment rates in the US hadn't remained at or below 4% for more than 6 consecutive months in recorded history yet had done so for roughly 2 years prior to March 2020 (FRED [C], 2021). Simultaneously, GDP and industrial output appeared to be stagnating, whilst inflation had begun to rise towards the end 2019. Internationally, China's debt crisis remained a persistent concern and Europe was faced with the uncertainty that Brexit would inevitably bring; all evidence that the global economy was not as robustly healthy leading up to the COVID-19 Recession as one may believe. These assumptions have a sizeable impact on a potential recovery path of the US should they be proven correct, a possibility which shall be discussed when later considering government responses.

Figure 3: Variable Relationship Scatterplots



Furthering the line chart observations and prior theoretical findings, the above Figure 3 presents a set of four scatter plots highlighting the existence of the pivotal relationships researched in this study. As one would expect, the unemployment rate in the Construction Industry will have a positive relationship with unemployment in other sectors due to the interlinking of industry processes and chains of supply. The existence of this relationship is vital to the premise of this study, which is concerned with the collapse of one sector of employment signaling longer-term employment issues on a cross-sectoral basis. Negative relationships between the Construction Industry and GDP, Inflation and Industrial Output are also distinctly apparent. This suggests that both Okun's Law and the Phillips curve aggregate unemployment conclusions are persistently observable within at least this form of sectorized unemployment. The extent of this relationship is of greater significance for GPD and Industrial Output than for Inflation Rate, again calling into question the relevance of the Phillips curve. Additionally, the significance of all four observations is likely to differ from industry to industry, requiring study of individual impulse response functions to confirm the strength of these key interactions.

4. Methodology and Statistical testing:

4.1 Unit Root Testing

A Vector Auto Regressive model was chosen to handle the specifications of the fourteen forecast sets due to its unrestricted and flexible handling of dynamic multivariate time series. A VAR model regresses a vector of time series variables upon lagged vectors of those variables (Hanck et.al, 2020). As found by Knotek (2007), by constructing and interacting unrestricted vectors of time series dependent and independent variables, forecasts should improve when compared to those created under the imposition of linear, single-directional relationships. Prior to estimating a VAR, the entering data's properties must be evaluated to correctly specify components of the model. Stationarity must be initially addressed. The additional non-unemployment data has been entered into the model in terms of percentage change, period-on-period, due to these measured variables innately trending positively with time. However, unit root tests must still be completed across the three model static variables and twenty-four model dependent unemployment variables to assure stationarity has been achieved and further differencing is not required. A traditionally robust method of identifying unit roots is the Augmented Dickey-Fuller (ADF) test. It takes an autoregressive process and dictates the hypothesis that if the absolute value of an estimated parameter interacting with the measured variable over time is greater than or equal to 1 then the series is nonstationary and has a trend relative to time. The augmented Dickey-Fuller test extends its usage to timeseries with correlation at higher order lags (Meron, 2016).

$$x_t = \rho x_{t-1} + \varepsilon_t \quad (1)$$

H_0 : The series is nonstationary if $\rho \geq 1$

H_1 : The series is nonstationary if $\rho \leq 1$

As discussed previously, macroeconomic data recorded between 2000 to 2020 will include crisis period observations from the Great Recession. There is a distinct possibility that this will manifest as a structural break within the training data and interfere with the validity of the results of an ADF test. As such, a further augmented model may also be necessary to validate the stationarity of these series. The Zivot and Andrews unit root test offers a solution by applying a dummy variable to each possible break date throughout the entire series, identifying a proposed break point when the ADF test's unit root test statistic is at its minimum identified value (Zivot and Andrews, 2002). Under this test method the null hypothesis is that the series has a unit root without a structural break, whilst the alternative is that a structural break occurs at an uncertain point in time without disrupting the stationarity of the series. Across all variables within the twelve models, the Zivot-Andrews p-statistic remains below the 5% significance level suggesting that the null hypothesis can be unilaterally rejected, all data in this study is considered stationary.

One would both observationally and theoretically anticipate these results given emerging evidence that unemployment in developed nations is predominantly long-run stationary around the business cycle (Khraief et.al, 2015). However, although this holds historically for the data in this study, it doesn't confirm that the hysteresis hypothesis will not have some bearing on a labor market overhaul which is poised to take place in the wake of the COVID-19 Recession. Whilst the shocks had a sectorally transitory affect from 2000 to 2020, there was never a catalyst which extended towards threatening the functional practice of an industry over that period. Thus, regarding the current pandemic recession, one should not ignore the potential value of labor market stabilization policy.

With the test series now definable as stationary, there is no longer a need to ascertain long-term equilibria relationships between model variables. Cointegration can only occur in non-stationary series, thus, a Vector Error Corrective Model is deemed unnecessary. Regarding this model's use of data containing structural breaks; this is founded upon a desire to capture crisis level forecast training data from close-proximity, post-millennium recessions. Considering the emerging evidence that structural breaks are frequently overly accounted for, or less relevant to forecast accuracy than previously assumed (Boot and Pick, 2020), the potential presence of a structural break will not influence the forecasting techniques of this study.

4.2 Lag Order Selection

To identify and specify the finalized parameters and therefore estimate this model, the optimal lag length for the VAR must be discerned. Underestimated lag lengths may lead to omitted variable bias, whilst overestimating will create the opposite effect, with over-parameterized results. Therefore, an accurate and individually selected lag length should be applied to each model. To achieve this result, four information criteria for lag order selection are considered in this VAR. Akaike Information Criterion (AIC), Hannan-Quin (HQ) Schwarz criterion (SC) and Final Prediction Error (FPE). Determining lag order suitability is essential in reducing forecast error and certain selection criteria are more suited to different data sizes and frequencies. According to Ivanov and Kilian's guide to optimizing VAR lag length selection (2005), the AIC tends to be better suited to forecast monthly data as found within this study.

Table 2 indicates the orders proposed by the four criteria. All AIC tests prescribed lags of 8 or 9, which makes logical sense, as it is unlikely that there is a sizeable variation in the timing of sectoral transmission mechanisms for unemployment across the industries.

	Lag Criteria			
	AIC(n)	HQ(n)	SC(n)	FPE(n)
Agricultural Model	9	8	1	9
Construction Model	8	8	2	8
Educational Model	8	8	1	8
Finance Model	8	5	1	8
Information Model	8	5	1	8
Leisure and Hospitality Model	8	8	1	8
Manufacturing Model	9	5	1	9
Mining Model	8	8	1	8
Professional and Business Model	9	5	1	9
Other Services Model	8	5	1	8
Transport Model	8	5	1	8
Wholesale and Retail Model	8	8	1	8

Table 2: Lag selection

4.3 Method

The general stationary VAR can be expressed as the following multivariate regression model:

$$VAR(p): \boldsymbol{y}_T = \alpha + \beta_1 \boldsymbol{y}_{T-1} + \cdots \beta_p \boldsymbol{y}_{T-p} + \gamma_1 \boldsymbol{x}_{T-1} + \cdots \gamma_p \boldsymbol{x}_{T-p} + \boldsymbol{\mu}_T \quad (2)$$

Specifying for each individual model and chosen lag order, it is possible to specify the following sector specific model for the Agricultural Super-sector:

$$VAR(9): \boldsymbol{AGR}_T = \alpha + \beta_1 \boldsymbol{AGR}_{T-1} + \cdots \beta_p \boldsymbol{AGR}_{T-p} + \gamma_1 \boldsymbol{GDP}_{T-1} + \cdots \gamma_p \boldsymbol{GDP}_{T-p} + \delta_1 \boldsymbol{INF}_{T-1} + \cdots \delta_p \boldsymbol{INF}_{T-p} + \varepsilon_1 \boldsymbol{IO}_{T-1} + \cdots \gamma_p \boldsymbol{IO}_{T-p} + \theta_1 \boldsymbol{RUR1}_{T-1} + \cdots \theta_p \boldsymbol{RUR1}_{T-p} + \boldsymbol{\mu}_T \quad (3)$$

Denoted as:

$$\boldsymbol{AGR}_T = \alpha + \sum_{p=9}^{k} \beta_p \boldsymbol{AGR}_{T-p} + \sum_{p=9}^{k} \beta_p \boldsymbol{GDP}_{T-p} + \sum_{p=9}^{k} \beta_p \boldsymbol{INF}_{T-p} + \sum_{p=9}^{k} \beta_p \boldsymbol{IO}_{T-p} + \sum_{p=9}^{k} \beta_p \boldsymbol{RUR1}_{T-p} + \boldsymbol{\mu}_T \quad (4)$$

Equation 4, AGR *T* is the current rate of agricultural unemployment derived from prior values of the endogenous variables, gross domestic product (GDP), inflation (INF), industrial output (IO) and the aggregate unemployment rate excluding the agriculture sector (RUR1). *k* denotes the lag length used to forecast the current rate and *p* the lag order of modeled linear combinations. μ is the error term of the model. The additional inclusion of centered seasonal dummy variables at a monthly frequency controls for the seasonal effects of the data.

Table 3: Vector Autoregression Estimates for Agricultural model

	Dependent variable:				
	y				
	(1)	(2)	(3)	(4)	(5)
Agricultural.Unemployment.rate.l1	0.361***	0.049**	-0.005	-0.014	0.007
	(0.075)	(0.023)	(0.012)	(0.035)	(0.009)
GDP.percentage.change.l1	-0.331	-0.471***	0.163***	0.230*	-0.085***
	(0.252)	(0.078)	(0.040)	(0.119)	(0.030)
Inflation.Rate.l1	0.393	-0.071	0.536***	0.417*	-0.018
	(0.469)	(0.145)	(0.075)	(0.222)	(0.056)
Industrial.Output.l1	-0.245	0.092*	0.012	-0.125	0.010
	(0.167)	(0.051)	(0.027)	(0.079)	(0.020)
Residual.Unemployment.rate.l1	0.862	-0.163	0.170*	-0.528*	0.863***
	(0.629)	(0.194)	(0.100)	(0.297)	(0.075)
....	....	....	....	....	....
Agricultural.Unemployment.rate.l9	0.079	0.033	0.003	0.033	0.007
	(0.075)	(0.023)	(0.012)	(0.035)	(0.009)
GDP.percentage.change.l9	0.042	0.108	0.062	-0.091	0.012
	(0.265)	(0.082)	(0.042)	(0.125)	(0.032)
Inflation.Rate.l9	-0.442	-0.066	0.060	-0.280	0.131**
	(0.461)	(0.142)	(0.073)	(0.218)	(0.055)
Industrial.Output.l9	0.088	-0.042	-0.030	0.005	0.002
	(0.157)	(0.049)	(0.025)	(0.074)	(0.019)
Residual.Unemployment.rate.l9	0.314	-0.078	0.039	-0.161	0.014
	(0.596)	(0.184)	(0.095)	(0.282)	(0.071)
SD1	-0.777	-0.257	0.411*	0.382	0.488***
	(1.542)	(0.476)	(0.246)	(0.729)	(0.184)
....	....	....	....	....	....
SD11	-1.868	0.124	-0.041	-0.689	-0.212
	(1.564)	(0.482)	(0.249)	(0.739)	(0.187)
Observations	233	233	233	233	233
R^2	0.982	0.396	0.705	0.857	0.999
Adjusted R^2	0.977	0.205	0.612	0.812	0.999
Residual Std. Error (df = 177)	1.609	0.496	0.257	0.760	0.192
F Statistic (df = 56; 177)	176.671***	2.074***	7.556***	19.019***	3,899.402***

Note: *p<0.1; **p; <0.05 ***p<0.01

4.4 Model Diagnostics

Table 3 details the abridged VAR estimates of the Agricultural model. Before these findings can be leveraged to conduct more critical analysis, the model diagnostics must first be completed to ascertain the potential existence of inconsistencies and biases. Analysis of model residuals will form the bulk of these diagnostic tests, investigating the presence of serial correlation, heteroskedasticity, model stability and general residual distribution. The stability of the models has already been discussed. Here, an Ordinary Least Square Cumulative Sum (OLS-CUSUM) test was applied across all models with somewhat mixed findings. Some models experience no apparent structural change across variables, whilst others reveal a minor break. This may negatively impact the accuracy of forecasts within certain industries but, given our prior assumptions, the presence of relatively minor structural breaks should not prevent further analysis. The Autoregressive Conditional Heteroskedasticity (ARCH) effect test is implemented to test for heteroskedasticity in each model. The p-value returned across each test was greater than the alpha of 0.05 (0.4691 in the case of the Agricultural model), suggesting there are no heteroskedastic periods within any of the models. Similarly, the asymptomatic Portmanteau's Test performed to investigate the presence of internal serial correlation concluded a rejection of the null hypothesis. Across all models the derived p-values were unilaterally greater than 0.05 once the test variables had their seasonal component removed (0.4118 for the Agricultural model). This would suggest that the variables are not autocorrelated, retaining their desirable unbiased and efficient properties. The final set of tests investigate the distribution of residuals across modeled variables. The chosen Jarque-Bera (JB) test investigates whether the residuals of a variable match a normal distribution. Again, across models there was some degree of test statistic variation, but universally, p-values lower than 0.05 were returned by the test. This would indicate that the residuals are not normally distributed, a concern for this specification's forecasting strength. Additional Skewness and Kurtosis tests affirmed that the multivariate model's residuals were asymmetric and contained extreme values, also resulting in p-values below the 5% level of certainty. This non-normal distribution likely stems from recessionary outliers in the data which are essential to the premise of the forecast. Unfortunately, these test results imply that all twelve models carry residuals which appear to act as more than uncorrelated white noise. This may indicate that the general VAR structure suffers from some degree of misspecification and any conclusive results should be treated with a greater degree of caution. However, a visual appraisal of the histograms of residuals produced by the data appears to indicate they are reasonably normally distributed across all variables and models, potentially indicating that the JB test's p-value may only be so low as a result of the relatively small sample size to lag order ratio. Whilst undoubtedly a diagnostic red flag, non-normality should not dissuade the continued analysis of these models.

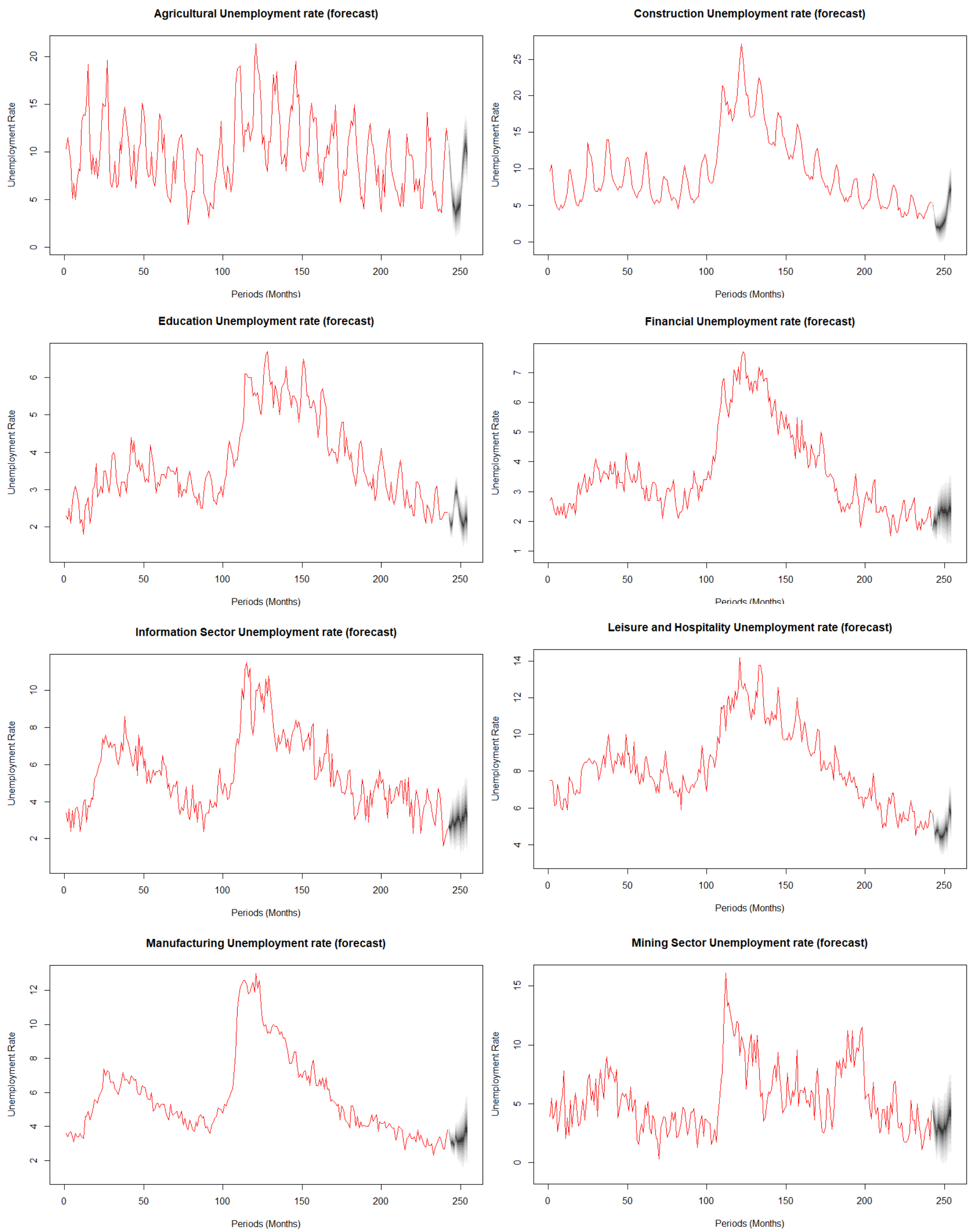
4.5 Analytical Tool Set

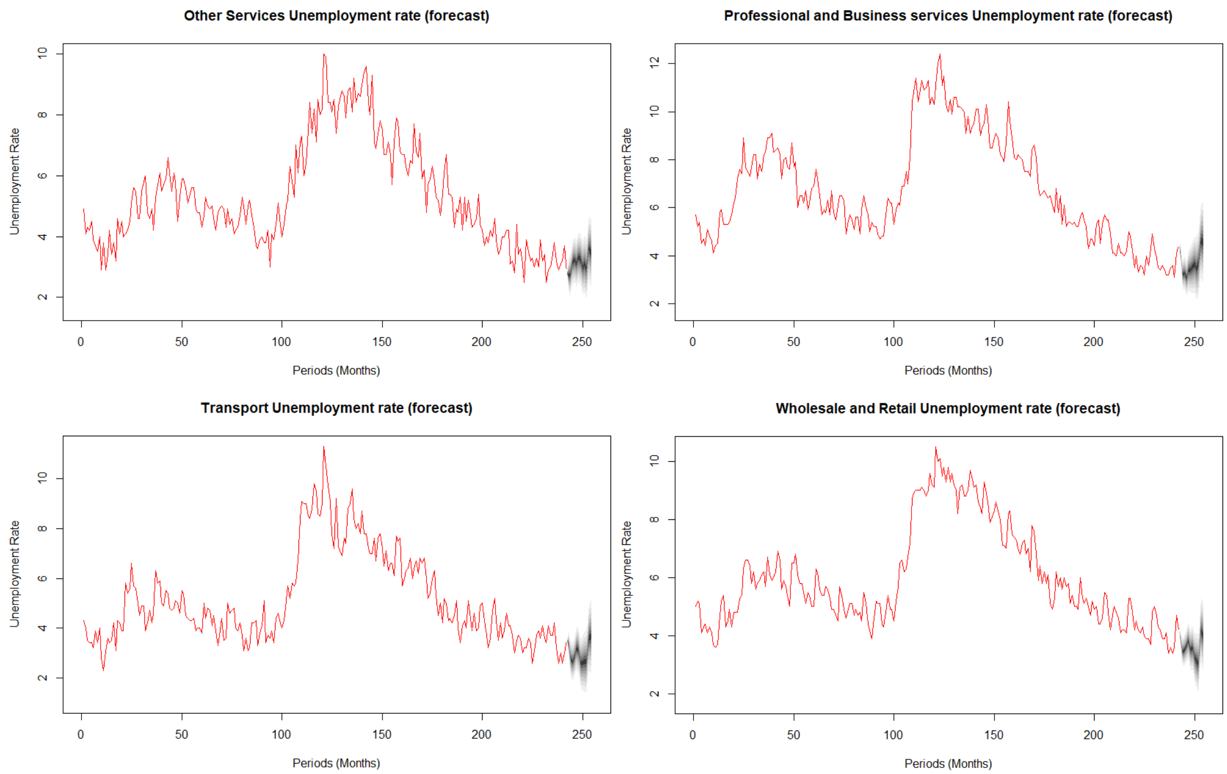
Commencing the application of the model's VAR estimates, fan forecasts will be constructed to propose the predicted continuation path of each variable from March 2020 to February 2021. Whilst forecasts for each specific variable will be reviewed for the purpose of inclusive model accuracy tests, it is the model specific sectoral unemployment rate forecasts which are of greatest interest to this study. From empirical observations of aggregate unemployment, it is doubtful that any model will be well suited to accurately predict the depth of sectoral unemployment experienced during the onset of the COVID-19 Recession, but will likely improve over the 12 month forecast period. Model forecasting performance which outperforms the naïve forecast will likely either be indicative of an industry with unique pandemic resistance or a rejection of the hypothesis that COVID-19 related sectoral unemployment is uniquely unpredictable and has not been transmitted through historically witnessed channels.

To augment forecasts, this study will leverage additional well established variable interaction tests to provide a more thorough understand of the relationships modeled. These robust methodologies will act as analytical companions to significantly derived forecast values and may grant additional insight into the transmission mechanisms through which macroeconomic shocks influence sectoral unemployment. Interdependence of variables in VAR models results in simple coefficient estimates lacking functionality when considering individual variable movements and shocks on a dynamic behavioral path. The first of these applied operations, is the Granger Causality test. This is a statistical test of correlation which implies the existence or non-existence of a predictive relationship between two or more variables. Pivotally, if a variable is shown to Granger cause another variable, that variable will be estimated more accurately using both the historic lagged values of the second variable as well as information garnered from the first variable. The nature or direction of causation is not specified. Simply, it determines a correlation between one variable's current level and the past value of another or group of others. The Granger test statistic within this multivariate study therefore seeks to confirm whether a set of regressed variables upon exclusively lagged values of themselves will have their predictive capacity improved by the addition of an external lagged variable of interest. A rejection of the null hypothesis signals the existence of a causal relationship between the test variable and other modeled variables and is drawn from a sufficiently positive interaction value attributed to the test variable. Within the bounds of this study, five Granger Causality tests will be conducted on each model to determine the existence of any unidirectional or multidirectional correlation supporting the presence of the theoretical macro-relationship foundations and informing targeted recovery policy.

The secondary tool of analysis leveraged in this study assists in gathering further information regarding the nature of any correlating relationship found to be present in a model. To decipher the direction, size and duration of a variable interaction, Impulse Response Functions (IRF) are employed. IRF's apply a synthetic positive or negative impulse to a modeled variable to emulate a real-world dynamic shift, such as a shock to aggregate demand or supply, as one would likely witness during a recession. The rate and size of this transmission of shock from the initially impaired variable to a secondary interaction variable will be reflected in an impulse response plot. To avoid understating contemporaneous reactions, Orthogonal Impulse Responses will be assessed in this study. The orthogonal method outputs a lower triangular matrix which is sensitive to variable order, Differing orders were tested to confirm the impulse response results were not statistically affected by the quirks of the methodology. As determining the responsiveness of sectoral unemployment to defined external impulses is at the core of this paper's aims, the impulses will be tested across all modeled variables but only the responses of the individual model's sectoral designation will be recorded. For example, a positive shock is applied to GDP, INF, IO and RUR and the response of each pre-defined Super-sector's unemployment rate (i.e.1) Mining, quarrying, and oil and gas extraction) is plotted thirty six monthly periods ahead with 1000 repetitions. The IRF results should allow for inferences to be made regarding the need and nature of targeted recovery policies within each industry. For instance, an industry which exhibits unemployment tendencies that move positively with shocks to other forms of unemployment may require more widely incorporated policies to recover, whereas another industry may be more demand dependent and require targeted sectoral stimulation.

Figure 4: Sectoral unemployment forecast fancharts





5. Results:

The twelve forecasts presented in the fancharts of Figure 4, predict the true month-on-month unemployment rate within the sector of employment specified for each model. Each is predicting outcomes across twelve future periods from March 2020 to February 2021, the first full year following the onset of the COVID-19 Recession. As seasonality is indexed back into the model, when evaluating the unemployment patterns portrayed by these charts, it is easiest to judge year-to-year data or by comparing prior seasonal highs and lows. From February 2020 to predicted levels in February 2021, unemployment is anticipated to rise within the Construction, Financial, Information, Professional and Business services, Transportation and Utilities, and Other Services sectors. The Leisure and Hospitality, Mining, Manufacturing and Wholesale and Retail trade sectors predict no unemployment shift over the year. Finally, the Agricultural and Education and health services sectors anticipate a minor fall in unemployment. In general, the sectors with higher natural rates of unemployment, as well as those more intensely affected by the Great Recession, were more negative in their forecasts. However, these February predictions are made at the lowest modeled confidence interval and should be treated as such. Another observable feature shared amongst many of the charts is seen in how all but the least seasonal industries, such as the Financial or Information sector, predict a post winter fall in unemployment followed by a summer or later winter incline depending on the seasonal nature of that employment. From this, it's possible to suggest that the predictive accuracy of these models was hindered by the timing of the COVID-19 Recession's onset, occurring during traditionally low unemployment months for most industries. In general, it would be fair to suggest the models are relatively pessimistic in their unemployment predictions, usually indicating greater unemployment highs than those experienced during the prior season's cycle. This is somewhat surprising when considering the descending unemployment recovery pattern all industries had been experiencing since 2010-11. Of course, the aim of these forecasts is not to make bold predictions, but rather to test how successfully the COVID-19 Recession can be modeled outright and thus answer key questions regarding its economic nuances and sectorally focused nature. As of writing, these twelve months have already passed, meaning data is fully available to judge the accuracy of these model's predictions.

Super-sector	Pre-COVID-19 MASE (March 2019- Feb 2020)	Post-COVID-19 MASE (March 2020 – Feb 2021)
Agriculture	0,4727618	0,4086644
Construction	0,2855376	1,733136
Education	0,3315048	7,100562
Finance	0,3522322	2,724983
Information	0,6854189	3,712337
Leisure and Hospitality	0,6793902	16,2622583
Manufacturing	0,2344529	2,3351025
Mining, Quarrying, and Oil and Gas Extraction	0,4773252	4,0899398
Other Services	0,2793054	8,2000661
Professional and Business services	0,3895445	2,8277872
Transport	0,3681448	7,1299965
Wholesale and Retail	0,4408855	6,0726297
Average	0,416375317	5,216455208

Table 4: MASE

Detailed in Table 4 are the Mean Absolute Scaled Error (MASE) values for these models. It is calculated by dividing the mean absolute error by the mean absolute error of the naïve forecast, which simply assumes the value at each point in time is the same as the prior historic value. This accuracy measure is employed to compare the predicative accuracy of all models, whilst also determining their relative value next to the naïve forecast for COVID-19 period analysis. A MASE value greater than 1 indicates that the naïve would perform better than the specified VAR model. Intriguingly, this is the case for all but one of the COVID-19 predictive models. The extended Agricultural model was relatively successful in predicting the outcome of the past twelve months with a MASE of 0.4087. This would imply that any conclusions regarding Granger Causality tests and IFR's from any model other than Agriculture's should be viewed with extreme skepticism. However, model analysis likely should not cease there. The reasons for the

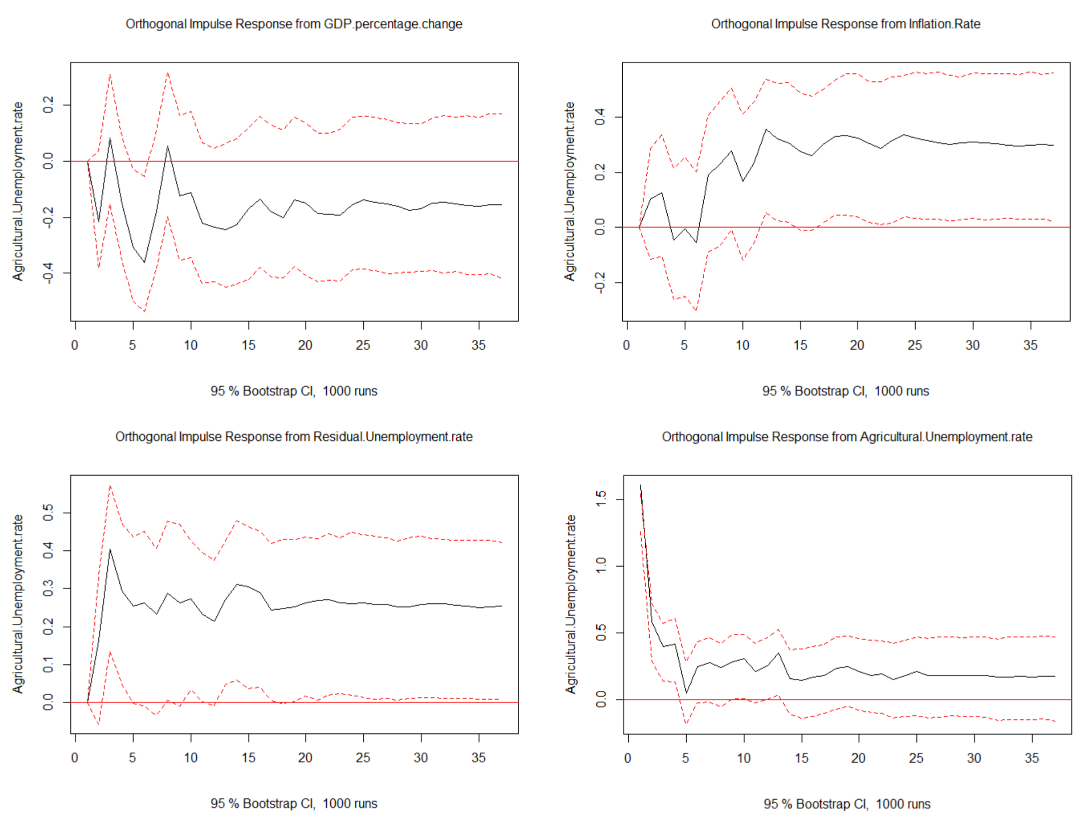
Agricultural industry's model outperforming all others despite almost identical specifications are immensely intriguing if one holds the assumption that employment is relatively homogenous across sectors. Furthermore, additional MASE's taken using forecasts derived by the same models and time series, but one year prior, indicate that predictive misspecification may only occur at crisis level. Thus, whilst not useful for modeling recessions such as the one proceeding the pandemic, identified shock impulses may still have sector specific relevance and should not be simply discarded in considering recovery period policy.

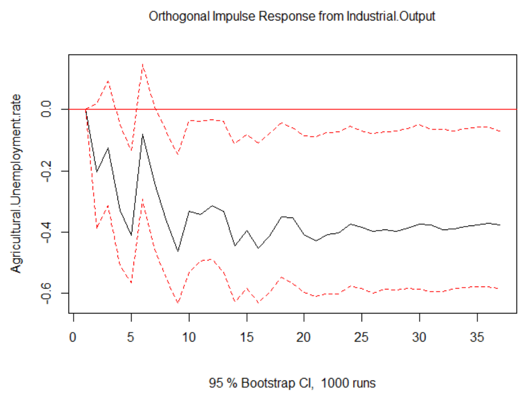
If one where to compare the differing fortunes of the models with the highest and lowest MASE, Agriculture and Leisure and Hospitality sectors respectively, as displayed in Figure 6, it should be immediately apparent that the defining struggle of this model occurs within the first three months of forecast. Cross analyzing the official sectoral COVID-19 data up until February 2021, it is clear that the unemployment contrasts are stark. During this period, agricultural unemployment simply proceeds along its seasonal trend, as was projected by the industry forecasts, whereas leisure and hospitality jobs appear to be beset by an instantaneous spike to, not only period highs, but historic peace time highs of almost 40% unadjusted unemployment. Whilst all models undoubtedly underestimate unemployment levels across the duration of the year, it is this unprecedented spike into equally rapid recovery which looks unlike any pattern found within prior training data. What's pivotally unique about this spike, is how it occurs alongside movements of similar magnitudes in the other variables modeled. This is a departure from the historic and theoretical prevalence of shocks being transmitted to the unemployment rate over a duration. It would appear, due to the unique nature of pandemic related shocks, within most industries these mechanisms occur as statistical irregularities. Therefore, when moving into further discussion of these results, particular attention must be paid to those industries with exceptionally high instantaneous exposure. This may correlate with long-run complications as it signals a break away from traditionally transmitted employment effects which have been shown to return to a natural rate of low frictional unemployment as witnessed even after the alarmingly deep Great Recession. These results add to mounting evidence that the COVID-19 Recession is a unique sectoral recession, unforecastable at its onset. It's possible that employment in the agricultural sector is simply acting in a forecastable manner due to an apparent symbiosis with the quirks of a pandemic, both in resisting its adverse labor market effects and complimenting the consumer demands it induces.

Given the mounting evidence that suggests the Agricultural (ARG) model is predictively significant, it's desirable to perform the additional analytical tests specified above. The aim is to delineate the strength of the posited variable relationships to help further understand what interactions might have led agricultural unemployment to respond to well-documented recessionary effects in such a unique fashion.

Granger Causality tests were performed across all five model variables. The first determined that AGR does indeed appear to Granger Cause GDP, IR, IO, and RUR at a 95% confidence interval. It returned a p-value of 0.01732, lower than the alpha of 0.05 leading to a rejection of the null hypothesis. This is possible evidence for Okun's Law or the Phillips curve relationship being prevalent within this sector. Equally, it could determine that AGR is a sector with a wider influence on other forms of employment. Next, GDP was tested against AGR, IR, IO and RUR. The result was a p-value of 0.002703, again, rejecting the null and affording the conclusion that at a 95% confidence interval, GDP does Granger Cause AGR, IR, IO, and RUR. The following three tests performed on IR, IO and RUR return the corresponding p-values of 0.0751, 0.08025 and 0.3252 respectively. These are all greater than 0.05, meaning it is not possible to conclude that either of the three variables Granger Cause the other four in each individual test.

Figure 5: Impulse Response Functions – Agricultural Model





Augmenting the conclusions of the Granger Causality tests, IRF's were conducted and plotted to display the direct, unidirectional response agricultural unemployment experiences when exposed to shocks to other modeled variables. Figure 5 shows AGR's dynamic response to positive impulses in each. Across the IRF's there is somewhat of a shared cyclical pattern across the first 12 periods. This may be occurring as a result of Agriculture's outstandingly seasonal unemployment pattern not being fully captured by the generalized dummy variables in this model. A positive shock to GDP appears to negatively affect the agricultural unemployment rate over the 36-month test period. However, the confidence bands for this IRF straddle 0 and indicate that this negative influence is not statistically significant. IO has a similarly negative relationship with AGR which becomes marginally significant, in the long run, after 8 months. IR has an initially insignificant relationship which is at times negative as one may anticipate. After 12 months this relationship turns marginally significant to the positive side, indicating that inflationary pressure increases agricultural unemployment in the long run. RUR shock to AGR is positive within 5 months, but inconsistently significant after that period. Finally, ARG's dynamic response to a shock on its own value is initially highly positive as logic would dictate, but rapidly declines to insignificance after 4 months as other economic forces begin to dictate the unemployment path. Across the sector, the significance of all impulse responses was, on average, less pronounced than in other sectors, suggesting that unemployment in the industry is derived somewhat uniquely. A greater understanding of what is causing these abnormal results is pertinent not only to the long-term future of the agricultural industry, but also in aiding the industries which have reacted poorly to direct employment shocks.

6. Discussion:

6.1 Explanation of Results

Overall, the AGR model was comparatively very successful in predicting the one-year agricultural unemployment pattern and was still within the 1% total unemployment error range during the seasonal highs when estimating January and February 2021. Other industry models are predictively less accurate during the first 2 to 4 months of the estimated period, which is when their orthogonal impulse interactions are generally at their lowest over the 36 periods. This suggests that much of the wrongly predicted unemployment variation is sourced from outside the estimated macroeconomic indicators in this model, hence its failure to capture these future outcomes in training data. However, even the AGR model failed to predict the April 2020 spike in unemployment and elevated seasonal high in June. Relative to other industry IRF's, agricultural unemployment was also far less statistically responsive to the test variables. Historically, it experienced a high natural rate of unemployment of around 10% when seasonally adjusted and was the industry with the greatest seasonal unemployment rate variation, of 9-10% per average cycle. As such, it enters the forecasting model from a unique starting point.

The above observations appear to signify two conclusions regarding the model specification and recession in general. Firstly, even as the only statistically predicative model, AGR fails like all other sectors to capture more acute COVID-19 Recessionary quirks. This indicates that pandemic driven recessions do not follow the traditionally observed channels of supply and demand transmission witnessed during events such as the Great Recession. As such, the assumption that sectoral unemployment during the COVID-19 outbreak is likely to reflect the path taken during 2008 is shown to be false, at least initially. This point is furthered through evidence from the non-significant industry forecasts as it appears that there are unknowns causing the initial model variations which are not well captured by the variables GDP, IO, INF or RUR. Secondly, unemployment in the agricultural sector appears to be heavily influenced by unique external factors. It is the only modeled industry that did not experience a meteoric initial increase in unemployment. It thus seems more predictively accurate despite the model rather than because of it. Considering these results, discussion intends to investigate the nuances behind the AGR observations and the sector's apparent resistance to pandemic effects alongside achieving a greater understanding of what makes the COVID-19 recession so difficult to predict and model. It's pivotal to consider whether the recession was driven by a true Black Swan Event, or if it was a White Swan Event which has illuminated the likelihood of future recurrences, as has been suggested by Nassim Taleb (Avishai, B. 2020). Furthermore, have these unprecedented events led to lingering consequences that may prevent the rapid employment recovery predicted by the Federal Reserve (Weinstock, 2020) and instead begin to mimic a more standard recessionary pattern such as that of the Great Recession after all? Irrespective, it is also worthwhile to identify and assess the industries most exposed to these unmodeled abnormalities to further understand their causes and likely consequences. Therefore, discussion will precede towards an analysis of the risk of long-term sectoral damage as a result of pandemic effects across all Super-sectors and proposed policy responses.

6.2 COVID-19 Recessionary Quirks

Global recessions are seldom homogenous in national synchronicity or cause. Yet, since World War 2 they have all been characterized by economic and financial disruptions within multiple large international economies and driven by a unique impulse catalyst in each case (Kose et.al, 2020). Shocks to commodity prices, financial markets and geopolitical uncertainty have typified the modern recession and are present within the timeline of the COIVD-19 Recession. Volatility in commodity and equity market prices rose rapidly during the outbreak of the pandemic, high corporate capital indebtedness has invoked memories of the irresponsible leveraged lending synonymous with the Great Recession and geopolitical instability has been both highlighted and exacerbated by the cross-border public health emergency (Cole and Dodds, 2021). Therefore, it was not a logical stretch to posit that the events of the most recent and severe global incident, the Great Recession, could have its recessionary indicators and sectoral unemployment paths reflected in the COVID-19 Recession. However, the results of this study would indicate that the current situation was impossible to closely model via prior recession data, outside of one sector which appears to be a major outlier. The pivotal failure of this model is in its assumption that all recessions are financially driven. Whilst the COVID-19 Recession seems to have been exacerbated by financial fragility and a wavering economic outlook, its antedating catalyst was the pandemic level public health emergency. Pandemic recessions appear to be unique in that it is the initial emergency legislation which emerges that dictates the timing and magnitude of recessionary effects. The vast global lockdown mandate now known as the 'Great Lockdown', brought with it unprecedented and instantaneous unemployment increases within every sector modeled. This transmission of unemployment was direct and unlike any recorded in historical data, making estimates untenable in the short term and explaining the failures of this VAR study. Functionally, unemployment in the initial months of the recession was downwardly capped at a Government dictated level depending on the precautionary risk level of the industry, teleworking feasibility and perceived importance to the continued function of the nation. A life-saving necessity but immensely disruptive supply side restriction with cumulative, cross industry supply chain effects. Whilst employment restrictions were accompanied by job and income retention schemes, such as the Families First Coronavirus Response Act and Coronavirus Aid, Relief, and Economic Security Act implemented in March 2020, uncertainty has remained rife. Pandemic relief assistance has been more accessible for individual claimants than businesses, leading to persistent threat of permanent closures for less digitally adaptive or smaller, more fragile businesses, as well as those operating out of more pandemic exposed sectors (Bartik et.al, 2020). Furthermore, eagerness to limit long-term economic and structural damage has led to COVID-19 striking in waves relative to the cycle of prevention policy intensity. Each COVID-19 cycle has heralded policy changes and mounting instability for the labor force, breeding uncertainty and conservative consumer spending. State level dictation of pandemic policy has furthered the nationwide inconsistency, likely cultivating wave-based infection transmission and distorting public policy expectations.

Cross-sectoral unemployment was at its most extreme when stay-at-home orders were in effect between late March and May, variable according to state legislation. As industries were allowed to re-open, they experienced rapid unemployment reductions that were just as unprecedented, statistically distortionary and sectorally unequal, as the initial rises. This recovery phenomenon was not driven by substantiated economic forces, but simply from the removal of pseudo unemployment-caps, hence the instantaneous month-to-month transmission. Initial recovery has accounted for over 50% of initial employment losses in most industries but should not be considered indicative of future unemployment recovery rates. More accurately, it signals a return to less restrictive employment markets and more familiar recessionary mechanisms. Furthermore, these recovery patterns are an additional hinderance to the capacity of predictive modeling for COVID-19 unemployment as Great Lockdown peculiarities are microcosmic and not captured by established economic mechanisms. Lockdown policies have manifested in reduced and uncertain incomes, inactive households and liquidity shortages, diminishing aggregate demand and perpetuating the issue. In this sense, the recession becomes more comparable again to the issues faced following the financial collapse in 2008. Therefore, the relevance of the modeled variable relationships in this study have not necessarily disappeared. Simply put, COVID-19 public health legislation and lockdown policy was so economically blunt, that more nuanced lagged interactions became difficult to capture statistically. These relationships may become pertinent again when considering historical long-run recessionary patterns once permanent infection prevention measures have been widely implemented.

Instead of unemployment being a lagged variable depending on external shocks to indicator variables conveyed by theoretical relationship foundations such as Okun's Law and the Phillips curve, unemployment itself appears to drive the economic downturn in the initial months of the pandemic. Additionally, the more comprehensive a state's lockdown policy, the greater the overall shock to unemployment and other economic indicators. For example, South Dakota didn't issue any business closure or stay-at-home orders and experienced only a relatively minor 6.3% adjusted unemployment increase from March to April, contributing to a fall in GDP of 8.13% from Q1 to Q2. Conversely, Illinois residents were issued with the lengthiest stay-at-home order as unemployment rose 12.8% in a month and GDP fell by 8.44% (BLS [D], 2021). Similarly, the industrial disparity of the COVID-19 Recession is further evidenced by state level unemployment patterns. In a state like Nebraska, where agriculture is the leading sector, unemployment rose only 4.3% in April and preliminary data from March 2021 indicates that it has recovered to below the 3.1% rate pre-recession. Comparatively, Hawaii, which is highly dependent on the leisure and hospitality sector was beset by a 19.2% unemployment increase initially and has only recovered to around 9% one year later (BLS [D], 2021). In total, relative state unemployment rates range over 6% in March 2021. This disparity expands upon the concerns regarding inter-industry inequality as much of this inter-regional effect appears to stem from the differing sectoral compositions of a state's economy. Dispersing economic fortunes tend to breed social distrust and resentment between regions and limit growth and stability, an addition worry that has been exacerbated by the COVID-19 Recession. Furthermore, it would be pertinent to question the reasons behind agriculture acting as an exception within this study. Historical data indicates that the industry is not regularly resistant to recessionary effects, therefore, it must be interacting uniquely with the effects of the pandemic. The nature of these interactions must be analyzed to not only better appreciate the true health of the industry, but potentially grant insight towards building future pandemic resistance into other industries.

6.3 Agricultural Sector's Pandemic Resistance

The US agricultural sector has unquestionably responded to the pandemic and ensuing recession in a fashion unlike any other industry in this study. Unemployment within the sector has moved closely with modeled VAR estimates and are not indicative of an industry in recession. The potential explanations for this individual outcome can be sourced to both internal and external industrial factors. At a base level of analysis, a vast majority of jobs in agricultural provision were deemed essential by the US Cybersecurity and Infrastructure Security Agency and permitted to continue during mandated closures (Krebs, C.C., 2020). The food supply chain is likely the most critically core system to a nation's infrastructure. This was especially highlighted during a pandemic crisis which limited freedom of movement and induced tremendous anxiety purchasing behavior with immense demand surges in basic utilities and food stuffs. Furthermore, the sector's domestic provisional burden was initially increased by import restrictions and global protectionism. As the industry tasked with absorbing many of these demand pressures and granted the governmental freedom to do so, it is somewhat unsurprising that Agriculture was resilient to a recessionary outcome. Reductions to the seasonal influx of H-2A migrant farmworkers due to visa processing reductions and travel restrictions were predominantly offset by high job mobility into the sector (Costa and Martin, 2020). Whilst agricultural unemployment is witnessed in this model to generally respond in kind to shocks to other forms of employment as a result of usual supply chain dependency, in this instance, the agricultural sector appears to have absorbed a portion of newly unemployed workers from other industries due to its perceived status as a secure form of pandemic employment. With regards to the other major impulses considered in this study, agricultural unemployment is generally statistically resilient in the short term, another factor allowing it to resist wider pandemic effects during the pivotal first months of the recession. However, unemployment during the peak agricultural season, between June and October, was between 1% and 2% higher than during 2019. This alludes to the interaction of lagged impulse relationships modeled in this study and displays the industry as resistant to the recessionary effects, but certainly not immune.

Aside from unemployment in the sector remaining low out of necessity, from a pragmatic, infection prevention perspective, Agriculture appears to be well suited on the surface. Whilst teleworking is not an option, a reasonable portion of agricultural labor takes place in open or external spaces. However, social distancing is ostensibly assumed in the industry and was likely not well adopted as an institutionally maintained practice within production lines. Further, governmentally conducted labor studies identified fewer than 50% of crop workers hold health insurance policies or belong to health plans provided by agricultural employers (Costa and Martin, 2020). This suggests that workers in the industry are more likely to return to work irrespective of symptoms of sickness, increasing the probability of self-perpetuating transmission. Research conducted by the US. Department of Agriculture has reported supporting statistical evidence of this, finding manufacturing and farming dependent counties to record the highest cumulative COVID-19 case rates across the nation (Pender, 2021). Additionally, this seems to be accentuated in non-metropolitan areas, suggesting that it is an apathy towards infection prevention measures, rather than population density, which appears to more so increase COVID-19's transmission rate. This is particularly alarming as the agricultural sector continues to operate as usual, out of a sense of urgent necessity and assumed natural pandemic resistance. Partially stemming from food and agricultural sectors employing a proportionally higher number of historically marginalized ethnic worker groups who have suffered higher mortality and infection rates during the pandemic, relative excess mortality was recorded to be 39% higher in food and agricultural workers in one Californian study (Chen et.al, 2021). An alarming discovery which may also indicate that the industry has maintained its comparatively low unemployment rates during the pandemic at the proportional cost of human life.

Considering the industry from a more medium-term perspective, despite the favorable unemployment figures across the recorded period, total employment level figures released for March 2021 indicate a sectoral shrinkage is still taking place within the industry (FRED [D], 2021). This likely comes as a result of it enacting unsustainable crisis-level employment policies and in the wake of infection and mortality considerations. Surface level observations may lead some to assume that the industry has remained robust to pandemic effects and offered a bastion of employment to those with lower skill profiles in dire need. However, a more detailed analysis into the workings of the industry over the period reveals much of this sector's apparent normality was procured in an unsustainable manner and at the expensive of national public health. As the sector begins to unravel, the crop yield and environmental struggles experienced in years prior become more telling. Agriculture was already a poorly performing sector in terms of relative unemployment rates, never recovering to the rates seen prior to the Great Recession. This is one of the many reasons why the COVID-19 period was comparatively accurately forecast when modeled. High retaliatory tariffs and falling producer prices as production outstripped demand had already wounded the industry. What's concerning is that the pandemic may have supported employment in the industry rather than hindering it by alleviating the immediacy of the aforementioned issues. As a result, post pandemic recovery may now pose a greater challenge than the recession itself. In general, this paper argues for a reappraisal of how sanitation and distancing policies are enforced and perceived in the sector should they remain necessary. Furthermore, the sector's overreliance on H-2A temporary migrant workers may be leading to longer term effects that are not well captured by short-run, crisis level data. Readjustments should be made to employment strategies to further stabilize the industry and prevent excessive overtime and increased infection exposure in the event of a future pandemic.

6.4 Super-sector Risk level

Apart from Agriculture, which has been shown to have a unique sectoral relationship with the COVID-19 Recession, all other investigated US sectors were forecast unsuccessfully by the stipulated specifications of this VAR study. This was generally a result of unprecedentedly restrictive workplace policies, with local governments directly shuttering employment premises. The extent of these restrictions dictated the recessionary path of each sector. Whilst business location also factored into enforced unemployment, with less metropolitan municipalities tending towards fewer mandated restrictions, the bulk of national variability was dependent on the nature of the sector. Unemployment rates saw a sizeable increase across all eleven remaining sectors, yet the extent and duration of the contraction was sector dependent. Those industries for which work location was inconsequential, teleworking infrastructure was established or socially distanced operating capacity existed, experienced lower unemployment rates over the first year of the pandemic. A sector's pandemic resilience was predominately dictated internally and fixed at its onset. This meant that little could be done to directly improve the unemployment fortunes of a highly exposed industry and the inequitable worker outcomes were predetermined. Levels of resilience were also relevant to recovery timings and rates, meaning that, as the more recognizable, economically driven, recessionary supply and demand deficits occurred, more initially exposed industries were again struck the hardest. This has created a situation where pandemic exposure has led to perpetuated recessionary effects in those industries, hindering their unemployment and output recovery rates and leading to the initial stages of a potential K-shaped recovery. Were this to occur, the US risks facing entrapment within a higher rate of boom cycle unemployment where socially or culturally valued industries and trades becoming marginalized or lost altogether, alongside widening inequality at regional and national levels. These extreme outcomes explain the necessity for future pandemic proofing based on the lessons learned from COVID-19, especially in those intrinsically public industries that are so naturally exposed to pandemic effects. However, before considering reoccurrence, it would be prudent to identify those lagging industries and evaluate measures to mitigate their circumstances.

By leveraging the mean absolute scaled error test results, it's possible to identify which sectors have been impacted disproportionately, relative to modeled forecasts. Augmenting these findings with a rudimentary analysis of seasonally adjusted sectoral unemployment data, the severity and persistence of the sectoral shocks can be evaluated to categorize an industry's pandemic exposure and assumed risk levels over the course of recovery. Labor market recovery appears to commence between June and July

2020, preceding the reopening of many non-essential businesses and loosening of pandemic lockdown policies. From this period onwards, more economically founded recessionary patterns take hold as the recovery has slowed. So much so that at this stage of the COVID-19 Recessionary cycle, observable similarities with prior recessions have begun to manifest amongst the sectors. This indicates that following the initial, previously unobserved, short term direct labor market shock, the recession has diverged into one influenced by predominantly economic factors and may benefit from the impulse response results, modeled to accurately predict sectoral deviations over the regular business cycle. Using the exposure and recovery data, the twelve modeled Super-sectors have been categorized as either, Low-Moderate, Moderate-High or High-Extreme risk industries, expressly relative to the likelihood of lagged or incomplete recovery as a result of pandemic recession effects.

Within the Low-Moderate risk category are: Agriculture and related private wage and salary employment, Construction, Financial activities, Manufacturing, Professional and business services and Governmental Employment. These listed Super-sectors tended to not experience extreme levels of enforced unemployment relative to their average natural rate recorded in the 21st century. In most cases employment deterioration, relative to pre-recession months, was low and adjusted unemployment has recovered to below the data period average. These industries are unlikely to experience isolated long-term effects due to the COVID-19 Recession. Many of the Low-Moderate risk sectors experience inherent teleworking advantage, workplace resistance to viral transmission or are responsible for the output of a provision deemed essential to national stability and functionality. As considered prior, the US Agricultural sector faces a multitude of external destabilizing threats, unrelated to the pandemic. However, as an industry, it didn’t suffer from recessionary levels of unemployment as a result of closures, and therefore is not listed as a direct pandemic concern. Sectors such as Construction and Finance have maintained low sectoral unemployment rates throughout the crisis relative to those experienced in the Great Recession. Both industries have had continued operations during the pandemic facilitated due to accommodating socially distanced or remote employment. Any concern for declining construction employment in 2021 should be abated when one considers that it appears to stem from cancelled contracts due to uncertainty in the private infrastructural investment market (Agc.org, 2021.). This indicates the downturn is not caused by construction specific pandemic factors and that a wider, confidence-bolstering, economic recovery will benefit the industry. Furthermore, the Financial sector displaying such resilience in terms of provisional and operational capacity should mark a pivotal divergence in recovery path from prior financially driven recessions. Financial institutions’ continued ability to defer loan repayments, whilst supporting private investment and consumer demand should increase the rate of recovery and potentially aid in equalizing the recovery process across demographics and sectors of the economy. The Professional and Businesses Service industry's administrative and professional sub-sectors are equally well suited to teleworking, with 71.6% of employees able to do so during April 2020 (Dey et.al, 2020). Where remote employment is not possible in the professional service industry, as is the case for the Waste Management sub-sector, it has been granted essential status, mitigating unemployment increases. Waste management is critical in controlling the spread of the virus but maintained operations likely come at the cost of increased secondary transmission. Therefore, echoing the conclusions of agriculture, these reduced professional and businesses service sector unemployment rates likely negatively impact employee health. This suggests that the sectors require improved protective measures and policies to mitigate on the job infection, even if pandemic related economic concerns are minimal within the industry.

Beyond improving the safety of working conditions in essential industries during viral outbreaks, it may also be possible to leverage their enduring necessity to alleviate recessionary outcomes in other sectors. For instance, there may be opportunity for these industries to spearhead a wider and more equitable economic recovery by providing the demand for labor which is absent in other less pandemic resistant industries. This has been the case in the Manufacturing sector, as demand for US capital goods has remained resilient, leading to labor shortages in the industry. Comparative job insecurity and rising disillusionment with formal education under COVID-19 (Kluver, 2021), would suggest that a migration from ailing professions to the manufacturing sector may be a solution to aid nationwide recovery. Unfortunately, without solving the potential social burden of losses to forms of leisure and the arts.

The industries assigned to the Moderate-High risk group, are: Education and health services, Information, Other services, Transportation and utilities and Wholesale and retail trade. Statistically, these sectors tended to experience more severe enforced unemployment rates at the onset of the recession, reaching unemployment highs which exceeded those of the Great Recession. They have since recovered to within their 2010-11 peaks but remain notably higher than their 20-year period averages or February 2020 levels. Many of these Super-sectors have been directly affected by nuances of a pandemic-based recession and are recovering more gradually given sustained pandemic pressures or longer-term effects of exposure. This exposure is often derived from teleworking infeasibility, high proximity workspaces or direct implications regarding the transmission or eradication of the virus. Risk of permanent sectoral shrinkage is mitigated in these cases due to their infrastructural significance or adaptive capacity, which may limit the severity of long-term pandemic effects. The Information sector is somewhat of an outlier within this group as 80.4% of workers could telework at the beginning of April. However, of those who could not, far fewer were able to continue working at a premise, such that 37.3% of the additional unemployment was derived from just 19.6% of the entire sector (Dey et.al, 2020). These findings are likely explained by the publishing and motion picture industries being classified within the sector. These sub-sectors provide high proximity and demand elastic services. Great Recession figures further indicate that the information sector is a historically recession exposed industry, providing low necessity goods and services at a time of crisis. This non-essential status has been accentuated by the enforced closure of public viewing premises. High fixed costs and closure restricted income has led to furlough rates of greater than 90% across corporate and service level jobs in the motion picture industry, threatening to lead to long-term sectoral shrinkage if the media providers are left financially unable to reopen. The Other Services sector faces a similar concern, with a multitude of sub-sectors facing differing levels of pandemic exposure. As an incredibly amorphous Super-sector it includes funeral and personal care services alongside private household employment. These subsectors experienced exceedingly high rates of pandemic level unemployment due to their interpersonal requirements which were incompatible with most state's stay-at-home orders. Their recovery has also likely been limited by falling demand for services which entail the need for close proximity interaction, limiting the industry's recovery potential relative to perceptions of infection likelihood. Both the Transportation and Utilities and Education and Health Services sectors are of great national economic importance and at the frontline of managing pandemic transmission and case severity. Aviation has been directly affected by stricter border control policy limiting flight frequency and capacity, whilst ground vehicular transport provision has faced reduced demand from increasing teleworking rates and lockdown orders. General travel and use of public transport methods has been disincentivized by regional governments and workplace closures, leading to demand deficient unemployment in the industry being essentially governmentally endorsed. However, the retention of some degree of mobility services is also a necessity to support commuting to other essential forms of employment and the flow of necessary goods throughout the country. As such, the transport industry has faced differing fortunes depending on the nature of federal assistance or limitations set by the Department of Transportation. Education and health services is another Super-sector comprised of essential industries that are exceptionally pandemic exposed. Teleworking is feasible in the educational profession, but supplementary, non-instructional jobs in the education system are surplus to the requirements of remote learning. These temporarily lost jobs tend to come in lower income roles, again, widening the income gap of the pandemic. Furthermore, unemployment in higher education has increased at a more drastic rate, with the Pew Charitable Trust determining this to be a result of state funding cutbacks as educational provision's falling standards have led to reduced enrollment figures and increased pandemic specific expenses for testing and tracing (Rosewicz and Maciag, 2020). Alternatively, one would anticipate healthcare services to retain exceptionally low unemployment rates as the demand for pandemic related treatment rises with infections. This has not been the case, as office based medical employment, non-essential healthcare services and dental offices have experienced wide-spread closures due to their high proximity work environments and utilization of scarce personal protective equipment (McDermott and Cox, 2020). Other frontline employees, such as those based in long term nursing care facilities have experienced steady unemployment declines since the onset of the pandemic. This is likely due to a combination of COVID-19 infection and burnout from the immensely high intensity and risk work environment (Frogner and Skillman, 2020). Whilst a very well governmentally supported Super-sector, concerns regarding work environment safety and dissatisfaction in teleworking opportunity may dissuade prospective workers and create labor shortages in the wake of the pandemic, bringing disastrous long term socio-economic consequences. The final Moderate-High risk sector is one that was already undergoing seismic alterations prior to the COVID-19 outbreak. Wholesale and Retail Trade experienced initially high unemployment rates due to store closures and disruptions to the supply chain, which later manifested in demand deficits for a portion of retail goods. Irrespective, unemployment rates recovered robustly, led by increased usage of online storefronts and demand for domestically orientated goods to facilitate lockdown behaviors. Additionally, certain retail business which were deemed essential suppliers of crisis necessities, expanded their labor capacity to meet excess demand. However, as an industry, retail was already on an employment decline as of January 2017 (BLS [E], 2021). The retail storefront model was failing relative to online shopping, with automated online services requiring fewer employees to operate in total. As such, the seemingly robust recovery experienced by this industry is likely a product of industrial redistribution as many have left the retail labor force permanently. This is evidenced by fewer working in the industry now than were employed in it in 2013 (BLS [E], 2021). This contraction may have been hastened by the pandemic and require additional, costly retraining for the newly unemployed especially considering similar customer services roles are equally under threat in other public facing sectors as a result of infection prevention measures and attitudes.

The High-Extreme risk industries consist of Mining, Quarrying and Oil and Gas Extraction, alongside Leisure and Hospitality Services. Leisure and hospitality was the Super-sector most initially exposed to temporary closure unemployment, reaching 39.3% total unemployment in April 2020, a figure that was even greater for the arts, entertainment, and recreation subsector. Unemployment recovery has been relatively robust, returning to below the Great Recession peak by April 2021 as pandemic related restrictions have eased. However, this is at a compromise of the industry shrinking by 16.8% in terms of total employment total since February 2020 (BLS [F], 2021), an indication that the apparent unemployment recovery is bolstered by falling labor force participation in the industry. These discoveries are unsurprising as the leisure and hospitality lies at the forefront of pandemic exposure and has close links with other badly affected industries. Leisure venues are dedicated to profit-maximizing, high capacity and close proximity experiences, requiring in-person attendance to consume. They are also superfluous to infrastructural national preservation. Therefore, lockdown limitations and social distancing policies have impacted the short-run outlook of this industry more so than any other. Furthermore, the performance of the accommodation provision subsector is highly dependent on transportation industry and international travel restrictions, highlighting the additional dependencies of the industry. There is evidence to suggest that minority demographics are more frequently employed in this sector (Tuman, 2020), indicating that the risk of unemployment has been borne more intensely by these ethnic groups. The previously discussed rising economic disparity in the US is likely compounded by the inequitable pandemic exposure of the leisure and hospitality sector as low-income, unskilled forms of employment have been the first shed by firms aiming to secure post-pandemic security. Whilst businesses in the sector accounted for only 6% of US bankruptcy filings in December 2020, this is likely a result of increased capital market reliance as high yield bond insurance in the sector increased from $9.7 billion in 2019 to $35.3 billion in 2020 (Landsbert at.al, 2021.). This places the industry on a strict timeframe, such that sustained failure to return to pre-pandemic earning rates will place immense stress on the future of the debt laden industry and possibly contribute to undesirable strain on the financial sector. The industry requires a combination of structural innovation to enable consumers to return to high proximity environments safely and simultaneous technological breakthroughs in COVID-19 treatment and prevention methods, without which, the leisure and hospitality sector remains exposed to future pandemic developments and the stringency of accompanying government measures. This has deeper implications for the livelihoods of workers trained within the ailing sector and in the most extreme cases, the continued existence of socially valuable cultural experiences. In the absence of a structural overhaul, these venues may become economically and logistically infeasible to maintain in a world reliant on current infection prevention methods.

The mining, quarrying, and oil and gas extraction Super-sector is a concern for differing reasons. Whilst unemployment exposure was initially greater than that of the Great Recession in this industry, it is a lack of persistent recovery pattern which is most troubling and unique. The industry is experiencing higher 2021 unemployment rates than it did during the height of COVID-19 restrictions, suggesting that pandemic concerns persist and are being amplified by sector specific factors. This decline has occurred despite workers in the mining and refinement of essential supply chain materials being identified as part of the critical infrastructure workforce. This is partially a result of the unique logistics of the industry, requiring more detailed safety protocols as mine site employees operate in high proximity, closed environments. These precautions have enforced a scaling back of operations, with low-skilled employees facing a high risk of enforced layoffs in the exploration, extraction and operation as well as mine site decommissioning sections of the mining value chain (Ramdoo, 2020). It appears that the mining sector has failed to recover from lifted restrictions, in part, due to a continued sense of infection danger in the industry, alongside its sensitivity to the wider economic and political status of the nation. Labor requirements are non-static and tend to expand and contract relative to the mining investment cycle, a process which has been offset by the more urgent requirements of the COVID-19 Recession, likely contributing to these higher unemployment figures (Ramdoo, 2020). Additionally, a change in presidency and incumbent political party has shifted labor sentiment on the future of the US resource industry. President Biden has pledged to reduce and eventually phase out taxpayer subsidies directed at fossil fuel companies (Hall, 2020), a departure from President Trump's intentions to reinvigorate the mining sector. Furthermore, the industry has simply been shrinking in terms of real employment since minable commodity prices began to fall in 2013. The industry is re-tooling towards less labor-intensive operations and increased automation, a solution which should mitigate future pandemic related crises, but one which comes at the cost of operational jobs. As such, the pandemic has highlighted concerns of increased labor shrinkage in the industry. It is likely that the continuation of high unemployment rates, as opposed to a more extreme worker exodus, is motivated by mining companies fearing "backlash from workers and host governments," (Ramdoo, 2020) should labor-saving technology be prioritized during a labor crisis. Yet, the severity of the situation may accelerate adoption of mechanization and technological innovation such that the sector is more productively efficient and pandemic resistant in the future. This points to the inevitability of labor orientated mining sector shrinkage which will need to be externally absorbed by other sectors, rather than supported intra-industrially.

6.5 Policy Proposals

Regarding targeted policy adoption, the sectors identified as being at moderate to extreme risk of long-run shrinkage because of the current recession should be granted special fiscal and regulatory dispensation. Fiscal stimuli in the US have predominantly been non-specialized and general, or targeted sectors of the economy that are perceived to have an inherently higher value, such as the American Rescue Plan providing direct aid to education and healthcare programs (IMF, 2021). Super-sectors which lack operational contingencies during pandemic conditions are exceptionally exposed to revenue shortfalls and are likely to require direct bailout funds or partially forgivable grants to access the liquidity to maintain employee contracts upon reopening. Prior legislation, such as that enacted on December 21st, 2020 (IMF, 2021), only offered grants to small and mid-sized movie theater companies, failing to ensure job security amongst those working at larger firms. Crowdfunding offers another avenue to expand upon existing culture subsidies and should see governmental endorsement to ensure the preservation of societally significant forms of leisure endangered by pandemic conditions. Another notable factor of the pandemic recession is that low-skill jobs tend to be the most at risk, due to replicability of the human capital previously holding those positions. Industries exposed to many low-skill employment roles have experienced greater unemployment spikes because of the pandemic. Through funding the upskilling of these employees, they would be able to remain within the sector in more productively essential and pandemic-proofed roles. The mining industry would benefit from this greatly if automation should become more prevalent in the completion of manual work, post-COVID-19. Toward a similar end, the redesign of pandemic exposed workplaces and consumption habits would reduce the need for widespread closures and mitigate the impact of a future recurrence. For example, logistical issues with how public transport is designed for pure passenger capacity has enforced a reduction of service provision. However, an expansion of size and rate of service in the transport system, such that larger distances are always maintained between passengers, would limit the negative impact of a pandemic upon the industry and related sectors. Finally, cross-industrial solutions have paved the road to recovery in other countries and could be well leveraged in the US also. Quarantine hotels have become commonplace in countries such as the UK and Norway, enforcing a system of stricter transmission control, whilst aiding two struggling sectors of the economy. The aviation industry can offer more flights due to these measures enabling safer movement of passengers into a country and the accommodation industry benefits from receiving those passengers for a financed duration. Government subsidized, multi-industry policies offer a more organic transition back to service provision and may ease demand deficient sectors towards normalcy as infection fears are alleviated.

When considering policies to augment universal economic recovery, it is this paper’s view, that the COVID-19 Recession should not be perceived as an isolated pandemic driven anomaly or Black Swan Event. An economic malaise was already forming around systems which had remained flawed since the

Great Recession and many sectors were operationally insecure prior to exposure to recessionary stimuli. As such, the prerequisite conditions existed for a recession to easily take hold and be perpetuated through economically founded channels. This recession has been sustained further by pre-existing economic instabilities, many of which were exacerbated by inter-pandemic economic shocks and will require the full extent of governmental fiscal and monetary policy to overcome. Additionally, it would be fair to suggest that the US, alongside much of the rest of the world, were underprepared for a pandemic of this scale. The appropriate systems were not in place to prevent a collapse from the ground up, with educational attainment dictating the likelihood of enforced joblessness at an increased rate over the course of lockdowns and closures (Parkinson, 2020). Industries, heavily pandemic exposed, lacked feasible contingency measures to retain employees and maintain capital flows and weren't structured nor sufficiently funded to reorganize operations in the event of a pandemic. Furthermore, aid and relief acts targeting individuals via direct stimulus packages were poorly conceived to the detriment of highly pandemic exposed industries which were forcefully closed and unlikely to reap the benefits of any direct stimulus spending. Small businesses did receive targeted grants and low interest loans as well as employee retention incentives, but not enough was done to specifically assist ailing industries (IMF, 2021). These factors have led to individuals belonging to historically disadvantaged groups or employed within a significantly pandemic exposed industry, suffering more so than the general populace and widening national inequality in the US; with the wealthiest in society simultaneously benefiting from record stock market highs, the COVID-19 Recession's demographical and sectorally inequitable quirks are strong evidence for a growing Matthew Effect in the USA (Perry et.al, 2021). As accumulated advantage intensifies, an increasingly unequal society will demand a greater portion of the government budget is expended upon welfare measures, likely stunting long-term economic performance if these inequalities are not prevented from taking hold.

It is also important that the extent of unemployment recovery experienced thus far is well contextualized. Outside of the outlier in Agriculture, no sector of the US economy has returned to within 20% of its pre-recessionary level as of March 2021. The general labor market has certainly not recovered fully from enforced closures as the sustained unemployment deficit appears to increasingly stem from recessionary aggregate demand deficits rather than government mandates. Furthermore, even including Agriculture, employment levels are universally lower in 2021 than they were in February 2020, highlighting reduced labor participation and the longer time-frame economic contraction taking place. Within the industries more directly affected by pandemic closures and social distancing regulation, sectoral shrinkage may be inevitable in the absence of technological evolution or government support.

Most alarmingly, as the K-shaped pattern of recovery becomes more pronounced, with industries facing vastly different fortunes, there are additional growing concerns regarding the sustainability and permanence of this potential recovery. Beyond targeting policy towards these languishing sectors, the opportunity to retrain portions of the underutilized labor force in struggling industries poses a solution to fears of inequitable employment outcomes. By reallocating labor towards more robust and digitally adapted industries, future pandemic outbreaks will be economically mitigated. Non-intrusively redistributing the workforce from sectors that are passively declining in labor demands, as is the case with retail and mining, affords their modernized restructure, whilst maintaining total unemployment levels at a minimum. The wider sectoral evolution of the economy should be governmentally tracked to meet evolving consumer demand and environmental considerations which have been highlighted by the recent recessionary lapse.

From a more long-term perspective there is need, not only for redistribution, but also for changes in regulation regarding pandemic preparedness. Whilst too numerous to fully list here, the Independent COVID-19 Task Force created an exhaustive summary of pandemic preparation and response policies to be adopted in future. An essential plea was made for increased investment in critical initiatives for the prevention, detection, and response capability of the nation such that additional financing should be granted to state and local health systems, testing and isolation centers, as well as for the maintenance of an adequate Strategic National Stockpile (Burwell, 2020). From an economic perspective, many pandemic exposed industries also require specific structural investment to allow for the consistent provision of services in accordance with socially distanced regulation or improved teleworking infrastructure and digital access.

Turning an eye to the future of the US labor market, its path to recovery now seems to be highly dependent on public health stimuli and policy implementation and evolution. After an initial V-shaped recovery which has slowed in recent months, for certain sectors of the economy, the recovery appears to be mimicking the fallout of the Great Recession. Whilst systems of pandemic preparedness and response regulation must be overhauled to prevent a public health disaster of such magnitude occurring again, lessons should also be taken from the response to the Great Recession. A beleaguered recovery period was symptomatic of over regulation and an attempted re-engineering of the economic systems that were viewed to be at the heart of the financial crisis. Sweeping change, irrespective of how necessary it is, tends to be accompanied by extreme uncertainty leading to cautious investment and hiring practices from employers. These distortionary policies may be mirrored in 2021, as the desire to prevent a costly pandemic driven recession from reoccurring exceeds that for pragmatic economic policy. Instead, this study suggests initially targeting government support towards the industries identified as destabilizing to the recovery, whilst holding interest rates at a minimum and limiting restrictive fiscal policy. Progressive regulation should be incorporated after sufficient economic recovery, funded by an expenditure-based austerity plan to avoid the recessionary influence of tax hikes (Alesina et.al, 2019).

7. Conclusion:

This paper set out to investigate the predictive relevance of GDP, inflation, industrial output and the residual unemployment rate of external sectors upon the rate of Super-sector specific unemployment. It aimed to do so in the context of the COVID-19 Recession, interacting historic, 21st century data, including the period of the Great Recession, in a series of 12 VAR models. As one would anticipate, results varied across all Super-sectors, unsurprising given the differing nature of employment in each. On average, GDP and industrial output had a significant and sustained inverse relationship with sectoral unemployment rates, evidence for the prevalence of Okun's law amongst most sectors. Residual unemployment rate had a positive relationship across all but the most economically isolated Super-sectors of the economy and inflation had an inconsistent and often statistically insignificant relationship. Within the first 6 months following a positive inflationary impulse, sectoral unemployment rates tended to fall as the Phillips curve would anticipate, yet over time this became a positive or insignificant relationship. The Phillips curve is under increasing scrutiny as a modern economic indicator and its inconsistency at a sectoral level may be a result of the modeled data being far from tranquil, a variability shown to highly influence the significance of its relationship (Sovbetov and Kaplan, 2019). The predictive potential of these interactions was shown to be of value during non-crisis level data across all 12 models. However, when applied to the COVID-19 Crisis, only the Agricultural model was sufficiently accurate in its forecast. This suggests that these relationships lose significance under duress and that despite its severity and similar aggregate effects, the Great Recession does not provide a good template for the initial unemployment effects of the COVID-19 Recession. Furthermore, upon detailed analysis of the VAR estimates derived for the Agricultural sector, there is overwhelming evidence that its forecast results were anomalous relative to the modeled variables. Agricultural employment in the US was resistant to many of the pandemic specific shocks, avoiding shortfalls in demand and enforced closures due to the nature of the industry. As a result of maintaining sectorally normal unemployment rates, the industry has seemingly experienced elevated COVID-19 incidence and death rates (Lusk and Chandra, 2021). This suggests that more must be done to protect workers in industries deemed essential and possibly implies shades of the disaster that could have been amongst other industries had employment not been restricted.

A sectoral study was further employed to validate the predictions of the ILO, suggesting this recession would be highly inequitable in terms of relative Super-sector disruption (ILO Monitor, 2020). By analyzing forecast inaccuracies, Super-sector employment rates and cross-recessional patterns, these claims were discerned as valid. It was also possible to identify which sectors were the most at risk and formulate targeted policy responses from this data. From an unemployment perspective, the COVID-19 recession was extremely sectorally imbalanced relative to the pandemic resistance of its composite sub-sectors. These resistance factors included capacity for teleworking or socially distanced provision of services alongside institutional importance. The ILO was correct in identifying the leisure and hospitality sector as one at high risk of disruption, but failed to anticipate how the mining, quarrying, and oil and gas extraction industry would be impacted. However, sectors such as finance and professional and business services outperformed expectations, displaying how pivotal pandemic resilience has been to employment figures within the first year of the recession. This possibly points to how more economically driven issues have yet to manifest.

In general, it is all too easy to assume that with over 45% of the adult US population vaccinated (Ritchie, 2021) and adjusted unemployment now back at 2014 levels (FRED [C], 2021), fears of a drawn-out recession should subside. It is worth remembering that this rate is still over 1.7x higher than it was in February 2020 and the recovery has slowed immensely throughout 2021. The total US labor force has shrunk sizably and sectors like Agriculture may start to languish more-so once pandemic demand pressures subside. The recovery is built on gains made in Low-Medium risk sectors, whilst the strong performance of the financial sector is being leveraged to maintain struggling businesses in retail and leisure sectors and developing dangerous interdependencies. With the potential bubbles emerging in the housing and equity markets, recessionary fears may go beyond initial pandemic effects. To prevent these bleak outcomes, this paper recommends a two-pronged approach. Firstly, the targeting of pandemic effect exposed industries with fiscal stimuli to prevent an asymmetric recovery from occurring and avoid costly redistribution where possible. Secondly, a continuation of expansionary fiscal and monetary policy in the short-term to prevent a recessionary relapse as a result of the festering economic conditions prior to entering the recession. This should be followed by a period of pandemic related regulatory action and spending to prevent a statistically likely reoccurrence, better preparing industries that were previously highly exposed to pandemic effects.

The preliminary findings of this paper identify the unique nuances of the COVID-19 Recession and it's sectorally unequitable factors. To deepen understanding of these specific sectoral interactions, this study calls for the formation of richer, individually crafted Super-sector models. Using standardized aggregate effect models provides a solid base for comparison but fails in offering accurately predictive forecasts. Additionally, leveraging alternative measures of labor underutilization such as U-4 or U-6 in COVID-19 related studies may be useful in gauging workforce sentiment and identifying job-market frailties. Future studies may wish to consider long-term unemployment statistics when evaluating the performance of Great Lockdown policies and initial pandemic shocks to employment. This was an additional methodology considered by this paper but deemed not suitable for a study commencing so soon after the recession's onset.

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Appendix A: Additional Model Forecasts and Diagnostics

Cross-Model Stationarity Tests

Model (Variable)	Potential break point location	P-value
GDP	93	1,04E-05
Inflation	105	< 2.2E-16
Industrial Production	114	< 2.2E-16
Agricultural UR	106	< 2.2E-16
Residual UR (1)	103	< 2.2E-16
Construction UR	95	< 2.2E-16
Residual UR (2)	103	< 2.2E-16
Education/Healthcare UR	100	< 2.2E-16
Residual UR (3)	103	< 2.2E-16
Finance UR	97	< 2.2E-16
Residual UR (4)	103	< 2.2E-16
Information UR	107	< 2.2E-16
Residual UR (5)	100	< 2.2E-16
Education/Healthcare UR	100	< 2.2E-16
Residual UR (6)	103	< 2.2E-16
Manufacturing UR	100	< 2.2E-16
Residual UR (7)	103	< 2.2E-16
Mining UR	106	< 2.2E-16
Residual UR (8)	100	< 2.2E-16
Other Services UR	100	< 2.2E-16
Residual UR (9)	104	< 2.2E-16
Professional/Business UR	103	< 2.2E-16
Residual UR (10)	103	< 2.2E-16
Transport UR	101	< 2.2E-16
Residual UR (11)	103	<2.2E-16
Education/Healthcare UR	100	< 2.2E-16
Residual UR (12)	103	<2.2E-16

Table A-1: Zivot-Andrews Unit Root Test

Cross-Model Diagnostic Tests

Model	Asymptotic Portmanteau Test (P-value)	ARCH Effects Test (P-value)	JB-Test (P-value)	Skewness Test (P-value)	Kurtosis Test (P-value)
Agriculture	0,4118	0,4691	3,70E06	0,009695	2,83E05
Construction	0,6863	0,3168	0,0003926	0,03295	0,001297
Education	0,2681	0,2851	1,14E10	0,0006064	8,21E09
Finance	0,2251	0,2496	2,56E10	0,01213	7,07E10
Information	0,2388	0,3842	4,03E12	0,002717	4,64E11
Leisure	0,2266	0,453	1,75E08	0,0003725	2,87E06
Manufacturing	0,3541	0,2543	9,20E10	0,001904	2,20E08
Mining	0,6519	0,1983	3,33E16	0,0005339	1,30E14
Other Services	0,2294	0,2851	8,04E11	0,0002744	1,33E08
Professional and Business services	0,6998	0,6991	3,29E06	0,01212	1,95E05
Transport	0,4916	0,1918	1,14E07	0,001372	5,37E06
Wholesale and Retail	0,557	0,326	1,52E07	0,009278	9,22E07

Table A-2: Cross-Model Diagnostics

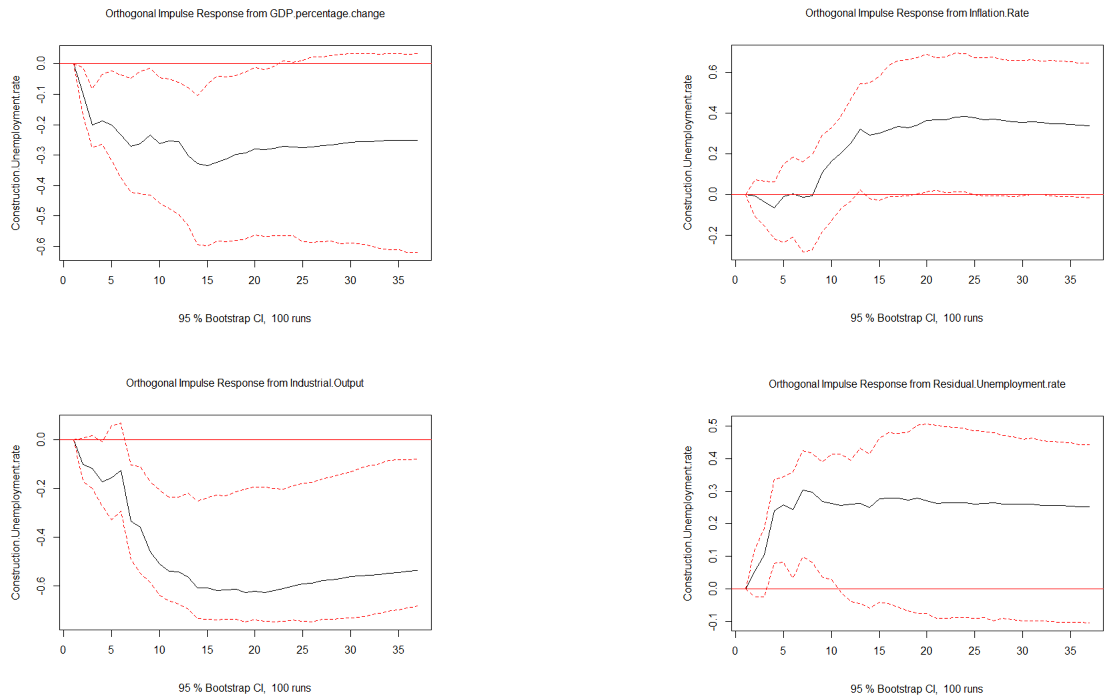
Test Variable	Granger Casuality F-Test	P-value
(Agricultural Model)		
Sectoral Unemployment Rate	1,5793	0,01732
GDP Change	1,8108	0,002703
Inflation Rate	1,3677	0,0751
Residual Unemployment Rate	1,0943	0,3252
Industrial Output Change	1,3571	0,08025
(Construction Model)		
Sectoral Unemployment Rate	3,1547	1,64E08
GDP Change	1,8797	0,002399
Inflation Rate	1,5716	0,02353
Residual Unemployment Rate	2,0819	0,0004523
Industrial Output Change	1,9918	0,0009651
(Education/Healthcare Model)		
Sectoral Unemployment Rate	0,73822	0,8549
GDP Change	1,9403	0,001473
Inflation Rate	1,3254	0,1085
Residual Unemployment Rate	1,5213	0,03294
Industrial Output Change	1,5726	0,02338
(Finance Model)		
Sectoral Unemployment Rate	1,3741	0,08221
GDP Change	2,2564	9,84E05
Inflation Rate	1,5275	0,03164
Residual Unemployment Rate	2,1691	0,0002129
Industrial Output Change	1,9853	0,001019
(Information Model)		
Sectoral Unemployment Rate	1,1977	0,2097
GDP Change	1,9696	0,00116
Inflation Rate	1,5096	0,03558
Residual Unemployment Rate	1,6922	0,01005
Industrial Output Change	1,6389	0,01475
(Leisure/Hospitality Model)		
Sectoral Unemployment Rate	1,5171	0,03388
GDP Change	1,9265	0,001649
Inflation Rate	1,2712	0,1452
Residual Unemployment Rate	2,3283	5,15E05
Industrial Output Change	1,3113	0,1172
(Manufactoring Model)		
Sectoral Unemployment Rate	1,8634	0,00172
GDP Change	1,7195	0,005784
Inflation Rate	1,5675	0,01893
Residual Unemployment Rate	1,3612	0,0782
Industrial Output Change	1,4779	0,03609

(Mining Model)		
Sectoral Unemployment Rate	0,61368	0,9555
GDP Change	2,2276	0,0001272
Inflation Rate	1,7427	0,00692
Residual Unemployment Rate	1,9184	0,00176
Industrial Output Change	1,3894	0,07515
(Other Services Model)		
Sectoral Unemployment Rate	1,2244	0,1843
GDP Change	2,0843	0,0004433
Inflation Rate	1,8737	0,002518
Residual Unemployment Rate	1,6067	0,01849
Industrial Output Change	1,5101	0,03545
(Professional/Business Model)		
Sectoral Unemployment Rate	1,4586	0,04123
GDP Change	2,0191	0,0004253
Inflation Rate	1,642	0,01072
Residual Unemployment Rate	1,2538	0,1476
Industrial Output Change	1,4498	0,04379
(Transport Model)		
Sectoral Unemployment Rate	1,4905	0,04026
GDP Change	2,6629	2,22E06
Inflation Rate	1,756	0,006262
Residual Unemployment Rate	2,0619	0,0005361
Industrial Output Change	1,4777	0,0437
(Wholesale/Retail Model)		
Sectoral Unemployment Rate	1,9602	0,001252
GDP Change	1,7115	0,008727
Inflation Rate	1,6044	0,01878
Residual Unemployment Rate	2,0609	0,0005406
Industrial Output Change	1,3495	0,09469

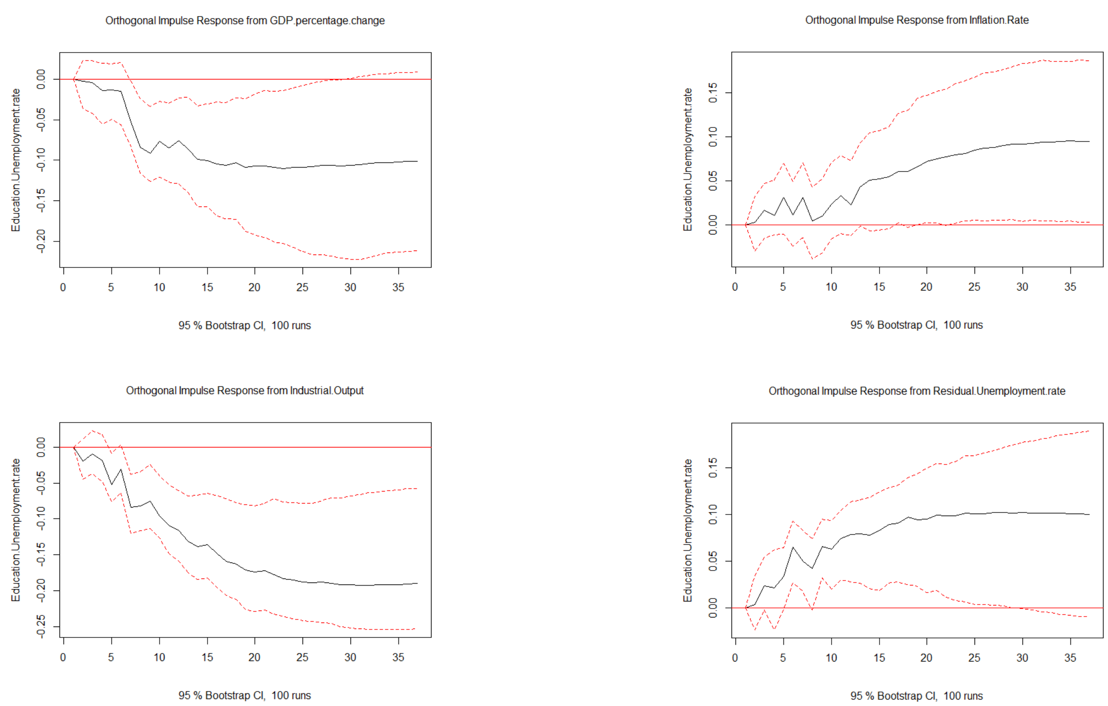
Table A-3: Granger Causality

Figure A-1: Extended Model Impulse Response Functions

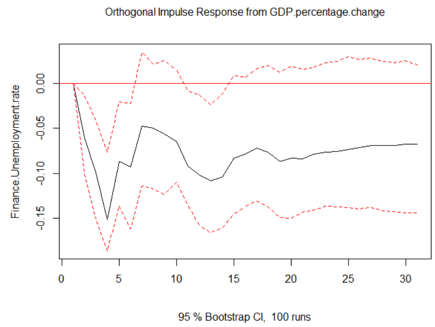
Construction Model IRFs

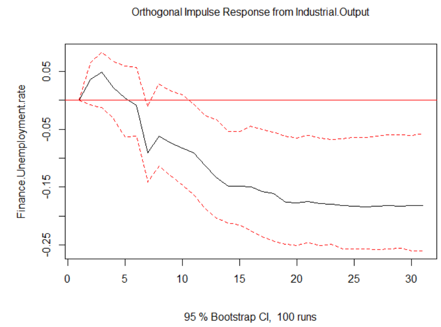


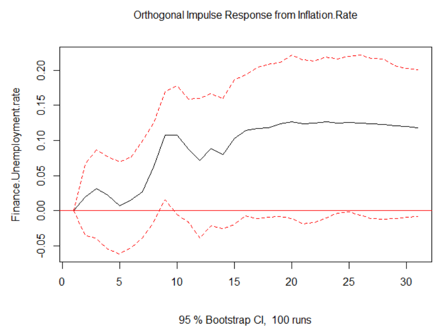
Education/Healthcare Model IRFs

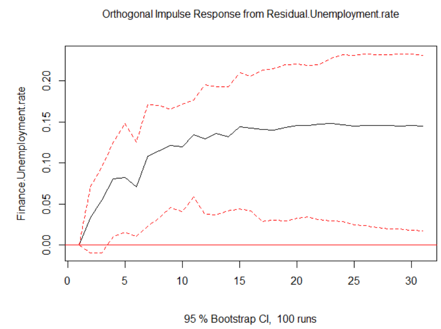


Finance Model IRFs

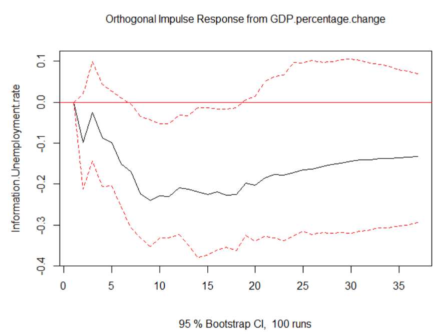


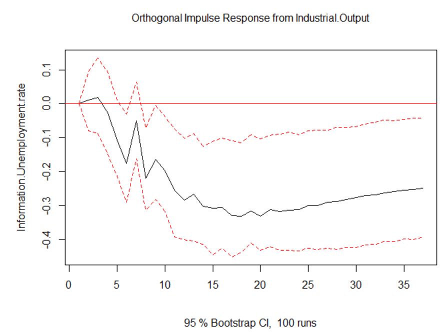


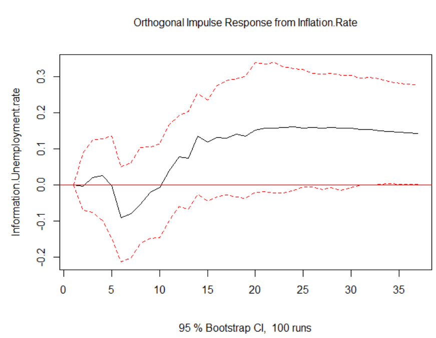


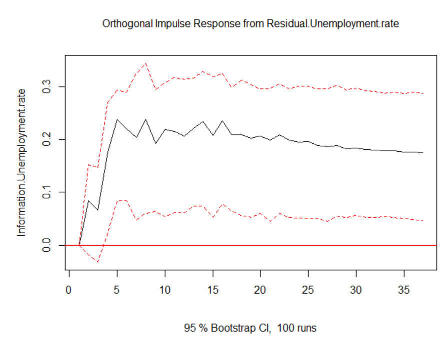


Information Model IRFs

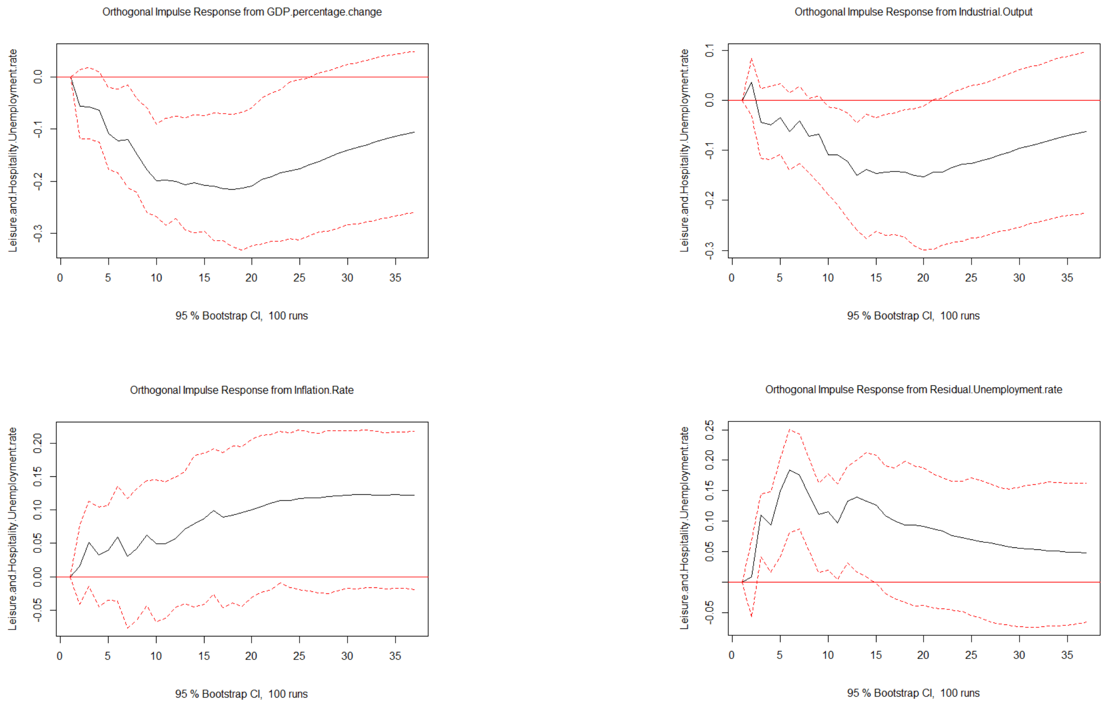




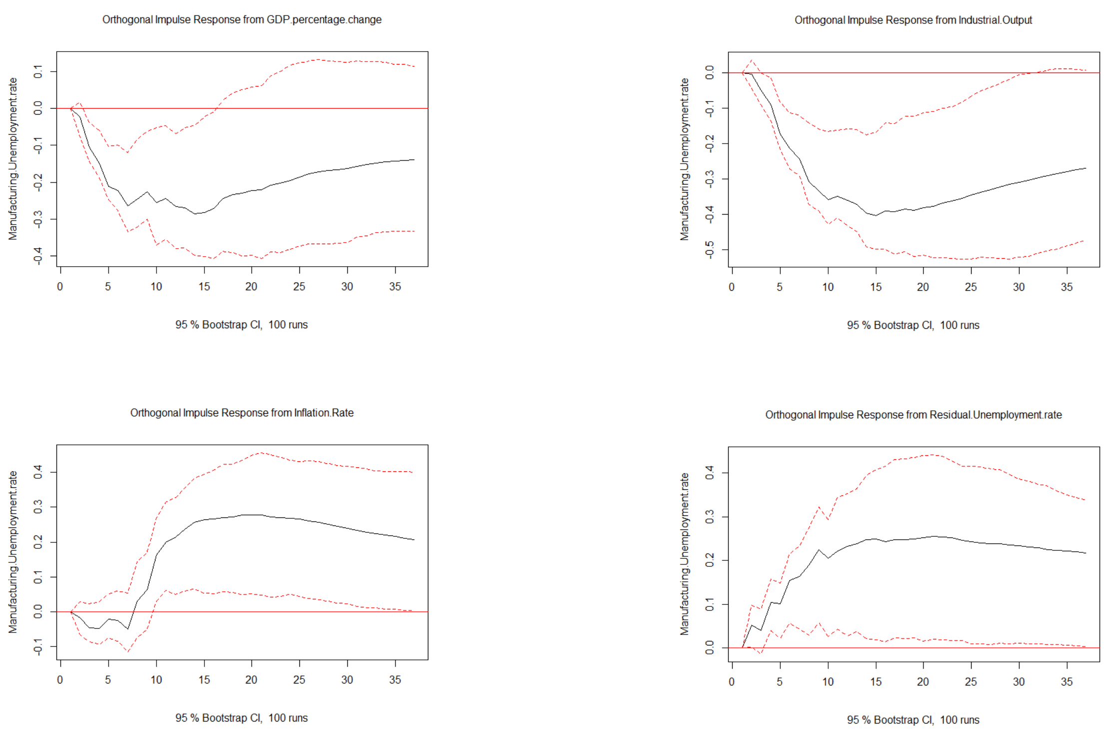




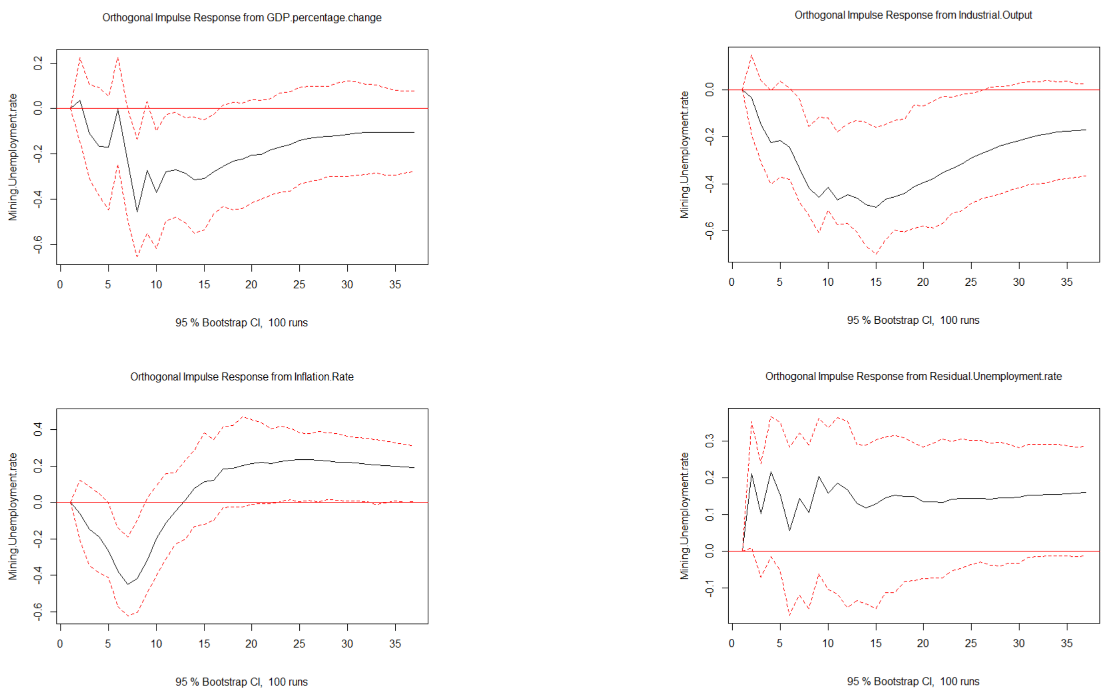
Leisure/Hospitality Model IRFs



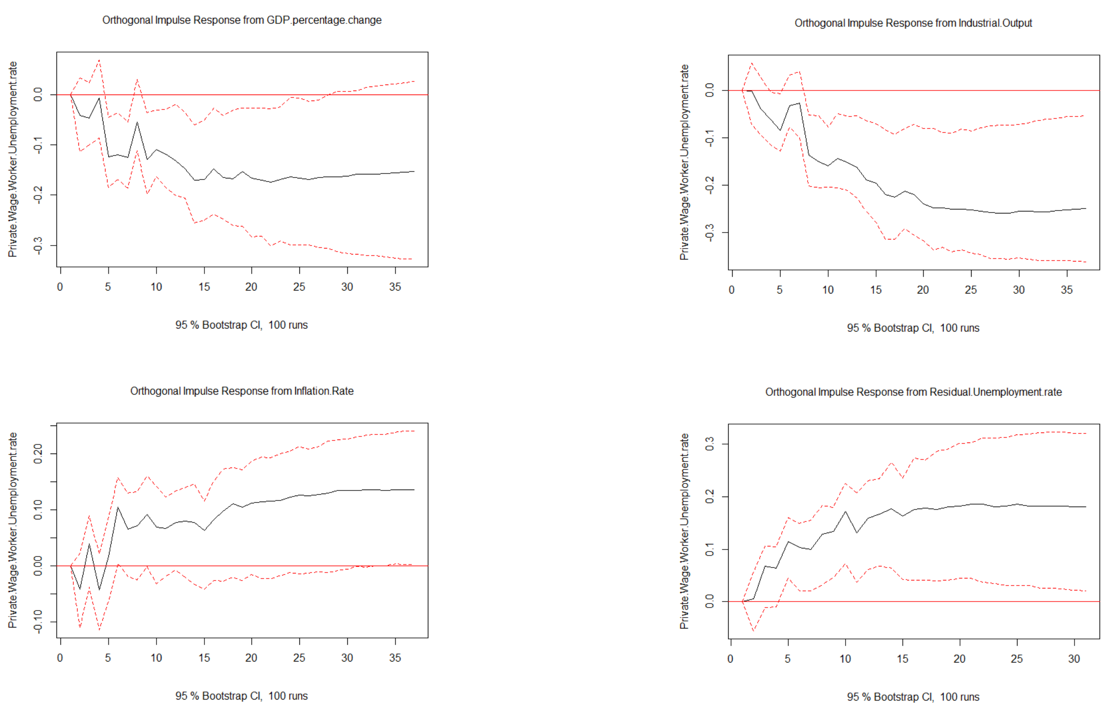
Manufacturing Model IRFs



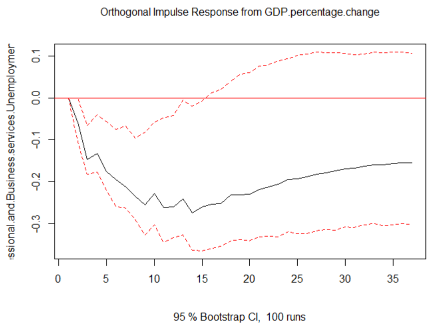
Mining Model IRFs

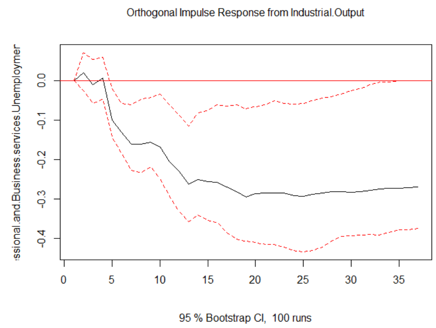


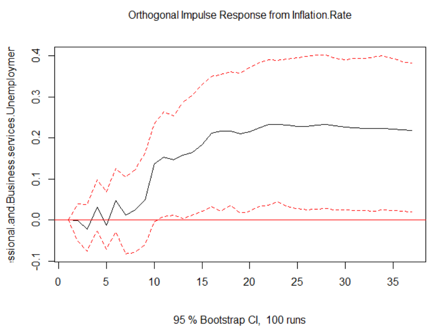
Other Services Model IRFs

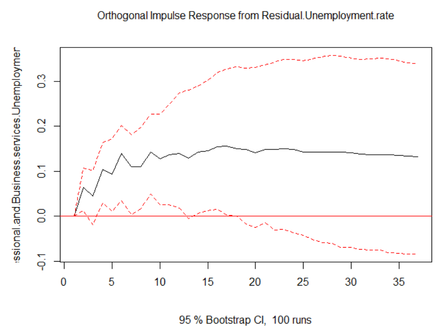


Professional/Business Model IRFs

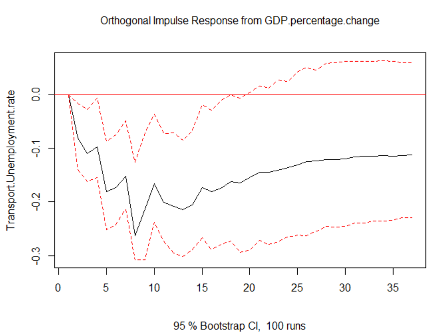


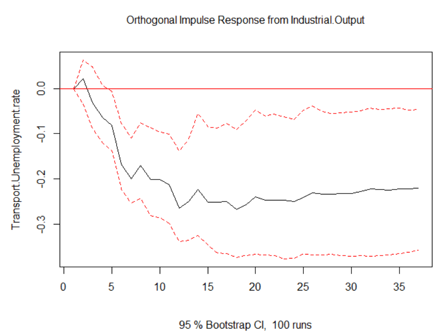


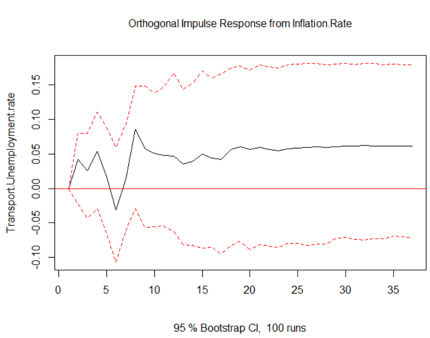


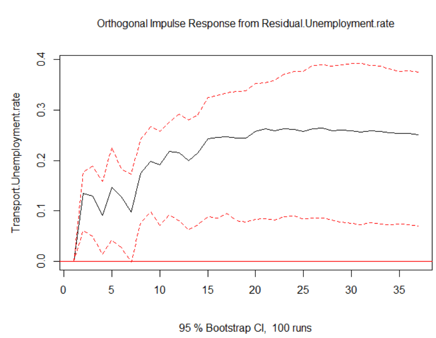


Transport Model IRFs

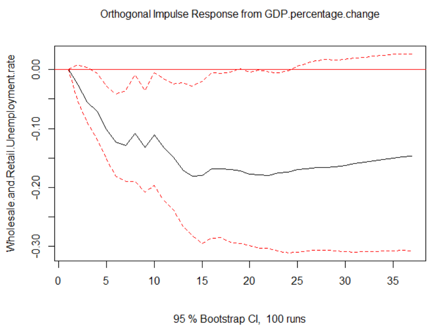


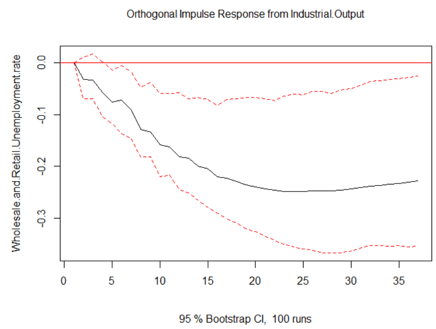


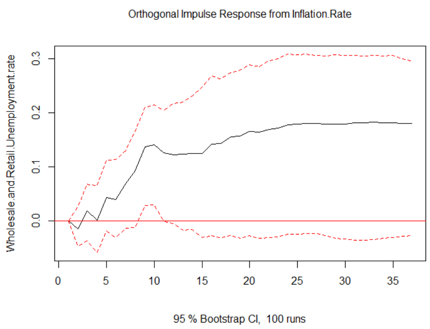


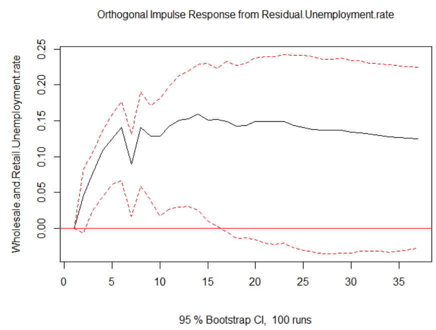


Wholesale and Retail Model IRFs









Appendix B: Data sources

All modeled series utilize non-seasonally adjusted monthly data unless stated otherwise. The data is derived from the Bureau of Labor Statistics (BLS), U.S. Bureau of Economic Analysis (BEA) and US Federal Reserve System (FED). It is accessible from the Federal Reserve Bank of St. Louis Economic Database (FRED), historic BLS database or IHS Markit monthly index archives.

Total Unemployment Rate: **Unemployment Rate (UNRATE)**, 01/01/2000- 01/02/2021, Source: US BLS

Sectoral Unemployment Rate: Data Retrieval: Labor Force Statistics (CPS), HOUSEHOLD DATA **- Table A-14. Unemployed persons by industry and class of worker, not seasonally adjusted (HISTORICAL DATA FOR THE "A" TABLES OF THE EMPLOYMENT SITUATION RELEASE)** 01/01/2000- 01/02/2021, Source: US BLS

Gross Domestic Product (percentage change from previous period): **US Monthly GDP (MGDP) Index,** 01/01/2000- 01/02/2021, Source: U.S. Bureau of Economic Analysis Data (monthly index created by IHS Markit).

Inflation Rate (percentage change from previous period): **Consumer Price Index for All Urban Consumers: All Items in U.S. City Average (CPIAUCNS),** 01/01/2000- 01/02/2021, Source: US BLS

Industrial Output (percentage change from previous period): **Industrial Production: Total Index (IPB50001N),** 01/01/2000- 01/02/2021, Source: US Board of Governors of the Federal Reserve System

Residual Unemployment Rate: Data Retrieval: Labor Force Statistics (CPS), HOUSEHOLD DATA **- Table A-14. Unemployed persons by industry and class of worker, not seasonally adjusted (HISTORICAL DATA FOR THE "A" TABLES OF THE EMPLOYMENT SITUATION RELEASE)** 01/01/2000- 01/02/2021, Source: US BLS