# Not All Economic Fluctuations Are Alike: Disentangling Their Effect On Labor Market Inequality

*By* Saul Richardson *

*Using a heterogeneous panel approach, I explore a set of prototypical economic fluctuations within the AD-AS framework and their implications for labor market inequality. Those fluctuations include aggregate demand and supply, monetary policy, exchange rates, and oil. I find that each economic fluctuation has distributional consequences across both race and geography. Black workers' sensitivity to macro fluctuations is reversed when it comes to demand– versus supply–side fluctuations. The effect of monetary policy on local labor markets is mediated by pre-existing geographical and demographic sensitivities to interest rate changes. Not all oil price shocks cause unemployment to rise, and the labor markets with higher employment shares in the secondary sector are most vulnerable to exchange rate shocks. Each of these findings would have been averaged out and washed away in an aggregate analysis, highlighting that the reality that labor market inequality is a local problem and must be studied as such.*

In the realm of macroeconomics and inequality, one would be hard-pressed to find a relationship more studied than that between Black workers and the rest of the economy. From figure 1, it's evident why that relationship has received so much attention: the Black unemployment rate is always twice that of White's throughout US history. Not only do Black workers face persistently lower rates of employment than white workers, but they respond more to macroeconomic conditions. Attempting to both quantify these gaps and learn what causes them to change has been a large goal in the literature on inequality and the business cycle.

*This thesis has changed more times than I thought possible. And while frustrating at times, I wouldn't have been able to find a topic that I enjoyed as much as this without the patience and tough questioning of Professor Kuttner. So, thank you! I am also very grateful to Professor Pedroni for teaching me how to think like a macro-econometrician. But most of all, thank you Umma. Thank you for everything. I miss you more and more every day.

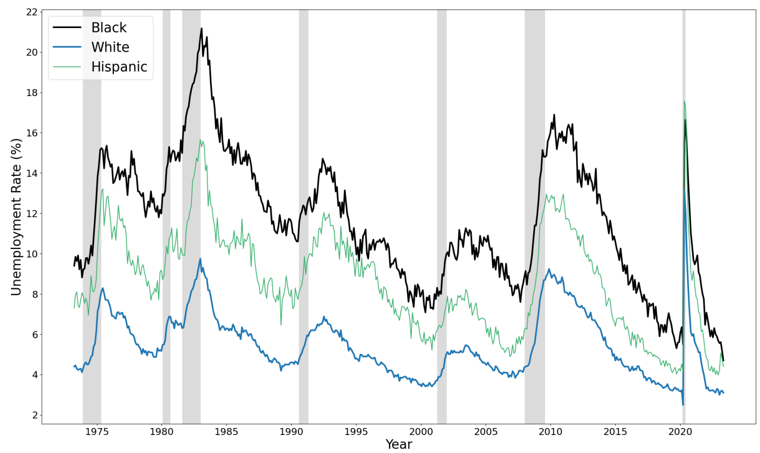



Figure 1: Unemployment Gaps

However, an important omission in this literature is that fact that unemployment gaps don't just exist across race but they also exist across geography. The interaction of the two will have important implications for how employment gaps like White-Black differentials respond to business cycle fluctuations. Labor market inequality in a place like Washington, D.C. where the Black unemployment rate is nearly three times the White unemployment rate will behave very differently than labor market inequality in Massachusetts where the Black unemployment rate is far less than 2x White's unemployment rate. In order to understand the heterogeneous effects of business cycle fluctuations, we must look across both race *and* geography.

The exact economic fluctuations I consider stem from three broad categories: aggregate business cycle fluctuations, policy fluctuations, and global fluctuations. The aggregate business cycle fluctuations I study are demand and supply at both the local and national levels. Then, I then move to more specific shocks often considered within the AD-AS framework. I begin with policy fluctuations in the form of monetary policy and then consider global sources of fluctuations in the form of exchange rates and oil. The disparate effects of these economic fluctuations have received considerable attention in the literature but only at the national level. There hasn't been much work on the localized effect of these fluctuations—giving us a unique opportunity to uncover how different types of metropolitan/micropolitan area respond to business cycle fluctuations. Section I details the empirical strategy of this paper and provides background on the macro-econometric methods employed. Section II details the data sources used throughout the paper. Sections III and present results and section IV concludes.

## I. Empirical Strategy

Often, the empirical approach in the inequality and business cycle literature is too descriptive—revealing only how unemployment gaps tend to move at different points in the business cycle but not revealing any causal connection between economic activity and inequality. This is because the strategy is typically to regress a measure of labor market inequality against some indicator for the state of the business cycle, e.g., a dummy for hot labor markets in Aaronson et al. (2019) or an indicator for the output gap[1] in Blinder and Esaki (1978). If we were to apply the typical empirical setup towards a panel of labor markets, it might look something like this:

$$\text{Employment Differential}_t = \alpha_i + \beta \text{ GDP Growth}_i + \lambda_i + \varepsilon_t \tag{1}$$

Now, there are a number of econometric issues with a specification. For one, estimating a single $\beta$ makes the unlikely assumption that each local labor market responds the same to GDP growth. Even if we indexed it by labor market, it wouldn't help much as then each labor market would be treated as independent of each other. That might work in a panel of individual microdata but in panel of interdependent labor markets where economic activity in one area will affect another, we can't treat each economic unit as unrelated to each other. There's also the issue of ignoring dynamics: GDP growth won't just affect labor market outcomes within the same time period but will impact them over time. All this is to say that $\beta$ can't be interpreted causally. At best, it just represents some association between economic growth and the employment differential of interest.

These issues of cross-sectional dependency, heterogeneous member responses, and endogeneity ultimately make a micro-econometric approach infeasible for the task at hand. So, I turn to a heterogeneous structural panel VAR technique that can address these issues and provide a causal connection between the economic fluctuations of interest and labor market outcomes. The exact technique takes on

[1] in the form of unemployment and inflation rates

two forms—a structural panel VAR (Pedroni, 2013) and a block structural panel VAR (Hao et al., 2017). The structural panel VAR is best suited for economic fluctuations that emanate from within local labor markets, e.g., aggregate demand and supply. As I consider more external sources of economic fluctuations, e.g., interest rates or oil prices, then the block structural VAR approach will be more appropriate. Both will allow for heterogeneous member responses, deal with cross-sectional dependency, and produce a causal connection between the economic fluctuations of interest and labor market inequality. Each method will give us the opportunity to breakdown the distribution of individual responses to economic fluctuations that is obscured when analysis in aggregate. In what follows, I will give a brief background on the macro-econometric methods being employed as well as the identification schemes used to disentangle the economic fluctuations of interest.

### *A. Preliminaries*

Structural VARs — The workhorse that underpins both approaches in this paper is the structural VAR. The motivation for any structural VAR is to conduct ceteris paribus experiments testing how an endogenous system responds to particular shocks. Consider the dynamic response of a vector of endogenous variables $\Delta z_t$ as specified in equation (2) where $R_j$ is a matrix of coefficients representing how $\Delta z_t$ responds to previous values of $\Delta z_t$ and $\mu_t$ is a vector of white noise residuals. Since everything is endogenous, it's not possible to determine—ceritus paribus—how changes in one variable within $\Delta z_t$ affect another because once one variable is perturbed, every other variable will change. Inference is unmeaningful. The solution is to invert the autoregressive form and put $\Delta z_t$ in terms of the white noise residuals $\mu_t$ ($2 \rightarrow 3$). Since each $\mu_t$ is now white noise across $t$, perturbing one shock in a variable won't induce the same endogenous feedback mechanism across time. We ask questions like what happens to X when

$$\Delta z_t = c + \sum_{j=1}^{P} R_j \Delta z_{t-j} + \mu_t \tag{2}$$

$$\Delta z_t = \tilde{c} + \sum_{k=0}^{Q} F_j \mu_{t-k} \tag{3}$$

The caveat, however, is that the white noise shocks contained within $\mu_t$ are not independent from one another, i.e., residuals within a single time period are correlated. Once one shock within $\mu_t$ is perturbed, the other shocks will respond—leading to the same difficulty as before. What we want instead is to be able to perturb an economic shock of interest, e.g., a spending shock, and see how our system of endogenous variables respond without other shocks also happening. In other words, rather than perturb a element of $\mu_t$ directly (and run into contemporaneous feedback), we need to perturb a shock that is independent from everything else. We can put some mathematical notation behind this in the form of (8).

$$\Delta z_t = \tilde{c} + \sum_{k=0}^{Q} A_j \varepsilon_{t-k} \tag{4}$$

Equations (8) and (9) look similar in that instead of modeling an endogenous system as a function of previous values, each models the system as a function of previous "shocks," but the shocks each model recovers are very different. Where $\mu_t$ in equation (7) was a vector of non-orthogonal statistical innovations, now $\varepsilon_t$ in equation (8) is a vector of the economic shocks we're interest. It contains i.i.d orthogonal processes, e.g., a spending or technology shock, that we can now conduct inference on.

So, we need a mapping from non-orthogonal statistical innovations $\mu_t$ to unobserved structural shocks $\varepsilon_t$. Perhaps most recognizable mapping is Blanchard and Quah (1989) who are able to map reduced form residuals from a system of output and unemployment into two structural shocks: aggregate demand and aggregate supply. They are able to do this by restricting one of the shocks to have a zero long run effect on output. With this, they are able to solve the relationship between the structural and reduced-form VMAs $\mu_t = A(1)\varepsilon_t$ and thus map shocks into those that have a long-run effect on output and those that do not.

Structural Panel VARs — Structural VARs allow us to disentangle transitory and long-run growth but to further decompose those disturbances into common and idiosyncratic components, I turn to the structural panel VAR methodology developed in Pedroni (2013). If a single structural VAR for just one member in a panel of countries is estimated, the structural shocks recovered will include both those that affect all members as well as those which only affect that specific member (what is referred to as composite shocks).

$$\Delta z_{it} = A_i(L)\varepsilon_{it} \tag{5}$$

But, a composite shock $\varepsilon_t$ is just a linear combination of the common $\overline{e}_t$ and idiosyncratic $\tilde{e}_t$ components so if we can recover either the idiosyncratic or common component, we can obtain the other. Pedroni adopts a common factor representation (10) in this spirit where $\lambda_i$ is a member-specific loading matrix[2] mapping how a common shock $\overline{\varepsilon}_{it}$ contributes to each member's own composite shock $\varepsilon_{it}$.

$$\varepsilon_{it} = \lambda_i \overline{\varepsilon}_t + \tilde{\varepsilon}_{it} \tag{6}$$

We can recover the common component by estimating a separate structural VAR using the common time effects $\Delta z_t^*$ where $\Delta z_t^*$ is computed as $N_t^{-1} \sum_{i=1}^{N_t} \Delta z_{it} \; \forall \; t$. Using the composite shock identity (10), this structural VAR will then take the form of equation (11). With some rearranging ($11 \to 12$), we can see how this procedure will only recover the common shocks by recognizing that the idiosyncratic shocks $\tilde{\varepsilon}_{it}$ are a zero mean i.i.d. process that is cross-sectionally independent. So, as $N \to \infty$, $N_t^{-1} \sum_{i=1}^{N_t} \tilde{\varepsilon}_{it} \to 0$.

$$\Delta z_t^* = N_t^{-1} \sum_{i=1}^{N_t} A_i(L)(\Lambda \overline{\varepsilon}_t + \tilde{\varepsilon}_{it}) \tag{7}$$

$$\Delta z_t^* = N_t^{-1} \Big( \sum_{i=1}^{N_t} A_i(L)\Lambda_i \Big) \overline{\varepsilon}_t + N_t^{-1} \sum_{i=1}^{N_t} A_i(L)\tilde{\varepsilon}_{it} \tag{8}$$

Rewriting the second term of (12) with this in mind causes the idiosyncratic term to drop out (13)—meaning that the shocks recovered in common time effects

[2] off-diagonals are set to zero, implying that a common can only map into a composite shock of the same type

structural VAR are only those common to all members of the panel (14).

$$N_t^{-1}\sum_{i=1}^{N_t} A_i(L)\tilde{\varepsilon}_{it} \to E[A_i(L)\tilde{\varepsilon}_{it}] = A_i(L)E[\tilde{\varepsilon}_{it}] = 0 \tag{9}$$

$$\Delta z_t^* = N_t^{-1}\Big(\sum_{i=1}^{N_t} A_i(L)\Lambda_i\Big)\overline{\varepsilon}_t \tag{10}$$

With the common and composite shock series in hand, we can now use (10) to recover the idiosyncratic series $\tilde{\varepsilon}_{it}$ as the leftover residual. And since each member's composite response is just a linear combination of its response to idiosyncratic and common shocks, we can decompose the composite response into the common and idiosyncratic responses (16).

$$A_i(L)\varepsilon_t = A_i(L)(\lambda_i\overline{\varepsilon}_t + \tilde{\varepsilon}_{it}) \tag{11}$$

$$A_i(L) = \overline{A}_i + \widetilde{A}_i \tag{12}$$

After each individual member's impulse response is estimated, there will heterogeneity in how members respond to common and idiosyncratic shocks, e,.g., some may respond more to common shocks $\overline{\varepsilon}_t$ than others. In other words, there will be a distribution of impulse responses. We can attempt to explain this heterogeneity by regressing the each member's impulse response against a set of characteristics. Collecting these characteristics in a vector $x_i$, we can fit the following regression via OLS (17) for each step $s$ of the response.

$$A_{i,s} = \alpha_s + \beta_s^{'} x_i + \eta_{i,s} \tag{13}$$

The variables more strongly associated with larger impulse responses can be seen as explanations for the observed heterogeneity, allowing us to see what might cause individual members to respond differently in a way that wouldn't typically possible with a fixed-effects regression.

Block Panel Structural VAR — The panel structural VAR is best suited to studying interrelated economies at a single conceptual level, e.g., studying the effect of financial development within the conceptual level of LICs (low-income countries). When one wants to study the effect of more external shocks, say the effect of US financial shocks on Cameroon GDP, then the methodology is less appropriate because in the case where an external variable and country-specific outcome have no endogenous relationship, the composite VARs will estimate the two variables as if they respond to each other. For instance, if we're studying monetary policy and local labor market outcomes, the Federal Reserve isn't responding to GDP growth in Detroit, Michigan. So, the federal funds rate and Detroit GDP shouldn't be modeled as responding to each other. The solution is to take a block approach where instead of everything endogenously responding to each other, we block any feedback from the local tier to the global. Essentially, this means treating each panel member as a small open economy. They can be affected by external variables like US monetary policy but are too small to move such variables themselves. The exact approach taken here is an extension of Pedroni (2013) introduced in Hao et al. (2017).

In Pedroni (2013), the composite structural impulses were decomposed into mutually orthogonal common and idiosyncratic structural shocks via a diagonal loading matrix. With the block approach, however, no loading matrix will be used to decompose common versus idiosyncratic shocks. Instead, we will use the variables themselves to identify common versus idiosyncratic shocks. To model each panel member as a small open economy, we have to modify the estimation algorithm. We can think of each system as being composed of a global block of variables as well as a member-specific block of variables (Ha et al., 2019). Instead of estimating all variables at once, we first estimate the global block separate from the local block. Then, we estimate the the entire system of global and local variables but do so in such a way that local variables cannot affect global variables. Lastly, we take the earlier estimates of the global tier and superimpose them on the entire system. This two step approach will block off any endogenous feedback from local variables to global variables when the PVAR is estimated. However, the same small open economy restriction needs to be applied with respect to the shocks as well. This is accomplished by restricting all unanticipated innovations in local variables to have a zero effect on unanticipated innovations in global variables for all time horizons. In other words, idiosyncratic shocks can't affect global shocks at all.

### *B. Business Cycle Fluctuations*

This first category of economic fluctuations considered will encompass the two classical shocks within the AD-AS framework: aggregate demand and supply. I will be using a panel structural VAR to decompose not only aggregate demand and supply shocks but also its idiosyncratic and common components.

Aggregate Demand & Supply — Why might aggregate demand versus supply shocks have distinct effects on labor market inequality? From a theory perspective, in the AD-AS model, output growth can be caused by either supply-side shocks, e.g., total factor productivity rises, or demand-side shocks, e.g., interest rates fall and spending temporarily rises. The effect of either on labor market inequality isn't immediately clear. In theory, a positive supply-side shock such as an increase in labor productivity would increase the real wage and entice more individuals to enter the labor force. However, a positive spending shock would cause a decline in the real wage with presence of sticky wages and thus lower the incentive for those outside the labor force to enter. From a theory perspective, both disturbances cause output to grow but their impact on labor market inequality is likely to differ as changes in the real wage will predominately affect the incentive marginally attached workers face to enter/remain in the labor force. This group of workers is largely made up of individuals from minority demographics such as Black, female, or less-educated workers (Bergman, Matsa and Weber, 2022)—meaning that there could be distinct distributional consequences of either type of fluctuation. The same can be said of the regional source of the shock. Common aggregate supply fluctuations like technology shocks might raise national output while specifically hurting employment in one region. But even putting theory aside, it seems perfectly reasonable to think that the types of jobs created from supply-side versus demand-side fluctuations will not only differ, but the demographics of the workers who get hired into those jobs will also differ. So, the effect of either type of economic fluctuation on labor market differentials (both across race and geography) is ambiguous and thus an opportunity for empirical research.

To uncover aggregate demand & supply shocks, I utilize the same zero restriction in Blanchard and Quah (1989), namely that the shock ordered second (referred to as aggregate demand) doesn't have a long-run effect on output.

$$\mu_{it}^{\Delta z_{it}} = A_i(1)\varepsilon_{it}$$

$$\begin{bmatrix} \text{Regional GDP}_{it} \\ \text{Regional Labor Indicator}_{it} \end{bmatrix} = \begin{bmatrix} . & 0 \\ . & . \end{bmatrix} \begin{bmatrix} \varepsilon_{it}^{\text{AS}} \\ \varepsilon_{it}^{\text{AD}} \end{bmatrix} \tag{14}$$

The structural panel VAR[3] is estimated at the MSA-level. The reason for focusing on local labor market outcomes is because the borders delineating a local labor market are constructed to encompass single entity with its own economic and social characteristics. They are meaningful. That's not the case with state boundaries which will encompass an amalgamation of individual labor markets, each with their characteristics and dynamics. Moreover, by further disaggregating down to the labor market level, we'll also have more heterogeneity among panel members—a useful property for uncovering a distribution of member responses. There are a variety of labor market indicators of interest,[4] e.g., Black-White employment gap, unemployment, hires. For this model, as well as those that follow, the system will be estimated separately for each indicator.

### C. *Policy Fluctuations*

The next category of economic fluctuations I consider are those that originate from policymakers. More specifically, I investigate the heterogeneous impact of monetary policy, in form of the federal funds rate, on labor market inequality using a block panel structural VAR. With monetary policy, there is already extensive literature using structural VARs to disentangle monetary policy shocks and quantify their potentially disparate effects on the labor market. Most have found only modest effects of monetary policy on employment as well as employment differentials (Carpenter and Rodgers III (2004), Bartscher et al. (2022)). However, this work is nearly all done at the national level and could be obscuring significant heterogeneity that washes out in aggregate data. Disaggregating down to the level of local labor markets will provide a unique opportunity to uncover potentially heterogeneous responses to monetary policy.

Monetary Policy — How might monetary policy affect labor market inequality? During the business cycle, a more accommodative federal funds rate might provide a greater benefit to marginally attached workers by boosting the economy

[3]For every system estimated, each variable is tested for a unit root and differenced accordingly. Also, the logarithm of each variable is taken before being inserted into the VAR, meaning that impulse responses can be interpreted as percent changes

[4]Different indicators have different unit root properties and thus may be differenced prior to being inserted into the VAR

and bringing them into the labor force when they otherwise would have stayed out. Remember that these marginal workers are largely made up of workers from low-income and minority backgrounds. So, preexisting gaps such as the Black-White unemployment gap might close with positive monetary policy shocks. By the same logic, however, contractionary monetary policy will hurt marginally attached workers relatively more than established workers as they're on the lower rungs of the employment ladder and most likely to be hurt in an economic contraction (Blanchard, 1995). Moreover, unskilled individuals are typically thought to have higher labor supply elasticities than skilled individuals (Blanchard and Katz, 1997)—meaning that a fall in labor demand due to slowing economic growth will have a larger effect on the employment level of these less-skilled workers. Since minority groups such as Black and Hispanic workers tend to have relatively less education and skills, contractionary monetary policy shocks could widen preexisting unemployment gaps (Thorbecke, 2001).

To study monetary policy, I will take the standard monetary VAR in the literature[5] and apply to a panel of labor markets. Local unemployment rates come at a monthly frequency whereas employment flow indicators only at the quarterly so two specifications will be used. The monthly specification will use real industrial production as its measure of economic output whereas the quarterly specification will use real GDP. To achieve orthogonalization, I impose a simple recursive structure on the system. Below, the zeros in black are the restrictions imposed to orthogonalize shocks at the global level. Unanticipated innovations in inflation are free to affect all variables in the system contemporaneously. Unanticipated innovations in output don't affect inflation contemporaneously, reflecting the idea of sticky prices. Unanticipated innovations in the federal funds rate do not have a contemporaneous effect on output or inflation. In other words, the federal funds rate is informed by developments in the economy but changes in the rate are only effective with a lag. Each shock is interpreted as orthogonalized general equilibrium innovations in the corresponding variable. The zeros in blue are imposed in order to orthogonalize local labor markets from the global block, i.e., to restrict unanticipated innovations in the local block from affecting the global block.[6] Here, as well as later empirical strategies, data on the global block of variables starts much earlier than the local block. So, to help with degrees of freedom, the global block is estimated over the period 1986-2022 and the local is

[5]This specification draws heavily form Carpenter and Rodgers III (2004)
[6]These zeros are placed at all time horizons, not just contemporaneously

done over 1990-2022 at both frequencies.

$$\mu_{it}^{\Delta z_{it}} = A_i(0)\varepsilon_{it}$$

$$\begin{bmatrix} \text{Inflation}_t \\ \text{Output Growth}_t \\ \text{Federal Funds Rate}_t \\ \text{Metro Labor Indicator}_{it} \end{bmatrix} = \begin{bmatrix} . & 0 & 0 & 0 \\ . & . & 0 & 0 \\ . & . & . & 0 \\ . & . & . & . \end{bmatrix} \begin{bmatrix} \varepsilon_t^{\text{INF}} \\ \varepsilon_t^{\text{US}} \\ \varepsilon_t^{\text{FF}} \\ \varepsilon_{it}^{\text{Metro}} \end{bmatrix} \tag{15}$$

### D. *Global Fluctuations*

The final category of fluctuations considered are those whose source is global, i.e., not just outside the realm of labor markets the way policy fluctuations were but influenced by factors outside the US economy. The specific sources considered are exchange rates and oil. I will be using a block panel structural VAR to disentangle both economic fluctuations. Both oil and exchange rates have received considerable attention with respect to their effect on output with some research on their disparate effects on labor market inequality (Kocherlakota and Pistaferri (2008); Elder and Payne (2023)). But, few have investigated the effects of either source within a panel of local labor markets. As with the previous categories, a theoretical framework for understanding how movements in either global variable might affect labor market inequality will be useful before delving into the weeds of the identification. The main channel through which both oil and exchange rates will affect local labor market outcomes (and thus affect labor market inequality) is likely to be the same: industry share. So, we'll apply the same theoretical framework for understanding how each might affect labor market inequality. I'll delve into the theory using exchange rates as an example but oil can easily be substituted in and the general ideas will still hold.

The most obvious point where the effect of exchange rates on local labor markets will begin to differ is the region's share of employment in industries dependent on global activity, e.g., local industries that export/import goods. Labor markets with a large employment share in such industries will see their input costs and profit margins shift more dramatically in response to exchange rate movements. For example, if a labor market is export-oriented, a dollar appreciation would be expected to reduce competitiveness, changing the ability of firms to hire and retain workers—potentially widening geographic unemployment gaps.

Beyond international competition, the impact of exchange rates will also depend on the product demand elasticity for a labor market's industry. If firms have to raise prices to offset movements in the exchange rate, but consumers are willing to substitute away from that firm's product, then firms might face lower profits margins and local unemployment rates could spike. Another mediator of the impact of exchange rates is the labor supply elasticity local industries face. If movements in the exchange rate boost profits so that firms are willing to raise the real wage to attract new workers, the benefits accrued to individuals in that labor market will depend on the how responsive labor supply is to changes in the real wage. Labor markets where industries face a high labor-demand elasticity with respect to wages will exhibit relatively more pronounced employment responses.

On the other hand, a dollar appreciation makes imports more affordable, potentially lowering the cost of input goods to local industries in such a way that some firms might benefit. Exchange rate movements might help one industry at the same time it hurts another all within one labor market. So, the effective impact is not at all clear from a theoretical perspective and provides another unique opportunity to for a heterogeneous panel approach that will uncover any disparate effects lost in aggregate data. All this can be similarly applied to the impact of oil on labor markets as it will also hinge on how significant of an input the product is to local industries. Since the main distributional aspect of either oil prices or exchange rates are the specific characteristics of local labor markets, I will not be disaggregating further than the regional level, e.g., race, and only look at inequality from a geographical lens. In other words, I will focus on the differences in how geographic unemployment rates respond to each shock rather than an employment differential.

Oil Prices — Looking at the effect of oil price increases on individual labor markets first requires asking what was the underlying cause of the price change. If we throw the real price of oil in a panel VAR, the innovations in oil prices could will be unexplained by whatever we put into the system but they could be caused by supply- or demand-side disturbances. We could be agnostic to the difference between supply versus demand driven increases in the price of oil but two are likely to have distinct implications for labor market outcomes, and knowing the difference will be important for implementing effective policy. High oil prices due to a global economic boom will surely affect hiring decisions differently than high prices due to negative supply shocks. Kilian (2009) was able to decompose movements in oil prices into oil-specific demand and supply shocks and finds, as one might expect, that the two differ in their effect on US output. So, it stands to reason that the same increase in the price of oil from one shock versus another will also have distinct impacts across labor markets.

The exact details of how Kilian constructs and defends his identification scheme is involved and better left to his paper. But, the interpretation of the structural shocks recovered from his short-run recursive identification will be discussed here. The following system is estimated at a monthly frequency—a key feature for he identifying restrictions.

$$\mu_{it}^{\Delta z_{it}} = A_i(0)\varepsilon_{it}$$

$$\begin{bmatrix} \Delta\text{Crude Oil Production}_t \\ \Delta\text{Real Global Economic Activity}_t \\ \text{Real Oil Price}_t \\ \text{Metro Unemployment Rate}_{it} \end{bmatrix} = \begin{bmatrix} . & 0 & 0 & 0 \\ . & . & 0 & 0 \\ . & . & . & 0 \\ . & . & . & . \end{bmatrix} \begin{bmatrix} \varepsilon_t^{\text{OIL SUPPLY}} \\ \varepsilon_t^{\text{AD}} \\ \varepsilon_t^{\text{OIL DEMAND}} \\ \varepsilon_{it}^{\text{METRO}} \end{bmatrix} \tag{16}$$

Oil supply shocks are defined as unpredictable innovations to global oil production given global activity and the real oil price. Global demand for commodities (called global AD for short) do not affect crude oil production contemporaneously, motivated by the delay between global economic activity and oil producer behavior. Innovations to the real price of oil unexplained by oil supply or global activity reflect changes in the demand for oil. This will include fluctuations in precautionary demand as well as changes in consumer preferences. Oil-specific demand doesn't affect global activity within the same month, reflecting the sluggish nature of the global economy to oil price increases, nor does it affect crude global crude oil production, reflecting the reality that oil suppliers are slow to adjust supply in reaction to demand. The global block is estimated over the period 1974m1 - 2022m12 while the local block is done so between 1990m1 - 2022m12.

Exchange Rates — The identification strategy used to disentangle the effects of exchange rates from movements in global activity and interest rates is built from Kilian and Zhou (2022). There, Kilian and Zhou estimate a much larger system than is necessary here but the same block recursive restrictions and variables are used.

$$\mu_{it}^{\Delta z_{it}} = A_i(0)\varepsilon_{it}$$

$$\begin{bmatrix} \Delta\text{Real Global Economic Activity}_t \\ \text{10-Year Real Interest Rate}_t \\ \text{RNEER}_t \\ \text{Metro Unemployment Rate}_{it} \end{bmatrix} = \begin{bmatrix} . & 0 & 0 & 0 \\ . & . & 0 & 0 \\ . & . & . & 0 \\ . & . & . & . \end{bmatrix} \begin{bmatrix} \varepsilon_t^{\text{US}} \\ \varepsilon_t^{\text{R}} \\ \varepsilon_t^{\text{RBXR}} \\ \varepsilon_{it}^{\text{Metro}} \end{bmatrix} \tag{17}$$

The block recursive structure has the following implications: unanticipated innovations in the 10-year US real interest rate have no effect on global real activity within the same month. This is motivated along the same lines as with monetary VARs, i.e., interest rates are typically thought to affect economic activity with a lag. The next implication is that unanticipated innovations in the real narrow effective exchange rate[7] do not affect global economic activity or real market interest rates within the same month. Both of these contemporaneous restrictions are motivated by the "well-documented disconnect" between changes in the exchange rate, inflation and domestic real activity (Mishkin, 2008). Under a stable monetary regime, such as that in the US, the transmission of exchange rate fluctuations to inflation should be negligible—giving little incentive for the Federal Reserve to change the policy or market participants to adjust expectations. Mishkin (2008) also shows that the response of output to exchange rate movements is relatively muted in an economy like the US, making contemptuous zero restriction on output more plausible. Both models for global fluctuations are estimated at the monthly frequency, helping keep it's short-run restrictions plausible. Both the global and local block are estimated with data from 1990m1 and 2022m12.

[7]narrow index is used rather than broad so that VAR can be estimated prior to 1992

### E. Second Stage Analysis

As detailed in section I.A, possible explanations for heterogeneous responses by individual labor markets can be investigated by regressing each panel member's impulse response against a set of static characteristics:

$$A_{is} = \alpha_s + \beta_s^{'} x_i + \eta_{is}$$

Finding a set of characteristics available for all 900+ metropolitan area will limit us to looking at aggregate and employment characteristics available from the QWI and Census Bureau. The following set of characteristics[8] will be used to explain the heterogeneous responses among local labor markets after each system is estimated.

$$\beta_s^{'} = \begin{bmatrix} \text{Primary Sector Employment Share} \\ \text{Secondary Sector Employment Share} \\ \text{Tertiary Sector Employment Share} \\ \text{Share of Population that has Bachelor's} \\ \text{Labor Market Tightness} \\ \text{Region} \end{bmatrix}$$

[8]Variables that change are averaged across time

## II. Data

The aggregate data sources on local labor market outcomes turn out to be quite good, often allowing us to disaggregate indicators by geography and demographic for 900+ metropolitan and micropolitan statistical areas[9]. The data for each labor market indicator comes from 3 sources: Quarterly Workforce Indicators (QWI), Job-to-Job (J2J), and the Local Average Unemployment Statistics (LAUS). The QWI contains a broad set of employment flow indicators, e.g., employment count, turnover, that can be disaggregated at the metropolitan/micropolitan statistical area as well the demographic level. However, the QWI's measure of employment flows is not well suited to conducting unemployment flow analysis because most of it will be driven by turnover.

In order to better approximate unemployment flows, I will use J2J's measures of hires and separations. This is because the J2J gives information on flows in and out of periods of persistent[10] nonemployment.[11] For instance, the number of Black workers who separated into a period of nonemployment longer than a quarter can be obtained for an individual MSA. So, I will use the counts of hires and separations out of/into a period of persistent nonemployment to construct what I will call "persistent hiring rate" and "persistent separation rate" for both Black and White workers. For instance, the persistent hiring rate is computed as the number of hires from persistent nonemployment divided by the total employment count. Effectively, this will capture the rate at which workers enter a period of nonemployment or leave a period of nonemployment. This won't be exactly the same as the job losing and job finding rates as it's not guaranteed that these flows into nonemployment are actually into the unemployed pool or into the non-participation pool. Nonetheless, these measures of flows will far less contaminated by turnover than the QWI's and thus closer to the job finding and losing rates only available with microdata. Both the QWI and J2J are reported at the quarterly frequency and are sourced from the Longitudinal Employer-Household Dynamics (LEHD) linked employer-employee microdata that covers over 95% of U.S. private sector jobs (U.S. Census Bureau, 1990-2022). The LAUS provides local unemployment rates for the 900+ metropolitan and micropolitan statistical areas at a monthly frequency (U.S. Bureau of Labor Statistics, 1990-2023).

The BEA produces a GDP series at the metropolitan level but it is at an annual

[9] both will be referred to as MSAs
[10] See table below for technical definition of persistent nonemployment
[11] J2J is only available for metropolitan statistical areas

frequency and only starts in 2001 (U.S. Bureau of Economic Analysis, 2005-2022). However, Moody's employs a very similar methodology as the BEA[12] to produce a quarterly GDP series for metropolitan statistical areas (MSAs) starting in the 1990s (Kamins and Ratz, 2017).

Table 1: Description of Labor Market Data

| Variable | Description |
|---|---|
| **Employment** | |
| *LAUS* | **Unemployment Rate:** The ratio of unemployed to the civilian labor force (1990m1 - 2022m12). |
| *QWI* | **Employment Count:** Estimate of the number of jobs on the last day of the quarter (1990q1-2022q4). |
| **Flows** | |
| *J2J* | **Persistent Hiring Count:** Hires following a spell of persistent nonemployment. A worker, i, is defined as a hire from persistent nonemployment to a firm, b, in a quarter, t, if i has no beginning-of-quarter main job with any firm in t-1 or t and has an end-of-quarter main job with b in t (2000q1 - 2022q4). |
| | **Persistent Separation Count:** Separations into a spell of persistent nonemployment. A worker, i, is defined as having a separation to persistent nonemployment from a firm, a, in a quarter, t, if i has a beginning-of-quarter main job with a in t and has no end-of-quarter main job with any firm in t or t+1 (2000q1 - 2022q4). |
| **Economic Activity** | |
| *Moody's* | **Real GDP:** Total economic output adjusted for changes in the price level. Available for 60 metropolitan statistical areas (1978Q1 - 2022Q4 ). |

[12]Similar in the se nse that it is a large econometric model that uses regional data and national aggregates to solve for regional GDP

## III. Results

### *A. Aggregate Demand & Supply Fluctuations*

The first category of fluctuations I will report results for are idiosyncratic and common aggregate demand and supply shocks. Three labor market indicators are used: White-Black employment ratio, White-Black persistent hiring gap, and White-Black persistent separation gap. A gap in a persistent rate is calculated by just subtracting the Black persistent rate from the White persistent rate. Movements in all three of these ratios will indicate how Black workers fair relative to White workers in response to aggregate demand versus supply shocks.

Employment Gaps — The first indicator is the ratio of White employment to Black employment. A decrease indicates the Black employment (relative to White employment) is growing more. Figure 2 graphs the cumulative response of the Black-White employment ratio to idiosyncratic aggregate demand and supply shocks while 3 does it for common shocks. Figure 4 presents variance decompositions. All responses are scaled to elicit similar sized movements in GDP.

What stands out the most is the heterogeneity in how the White-Black employment ratio responds to aggregate supply versus aggregate demand shocks. With an idiosyncratic demand shock, Black employment is growing relatively more than White for both the 50% and 25% quantile of responses. The median improvement in Black employment relative to White in response to an idiosyncratic AD shock is sizeable as the ratio decreases by than 10%.[13] However, there are some areas where Black employment is extremely more sensitive to short-run growth as the ratio for the 25% quantile declines much more rapidly. For the upper 75% quantile, however, Black and White employment grow at relatively the same pace.

All this stands in stark contrast to how the White-Black employment ratio responds to aggregate supply shocks. At both the common and idiosyncratic level, the median behavior of the ratio is to stay flat—meaning that neither White or Black employment is growing relatively more. However, for upper 25% quantile of member responses, White workers are benefiting relatively more and for the lower 25%, the reverse is true. The greater sensitivity of Black workers to macro fluctuations talked about in the literature is quite apparent with transitory growth:

[13]Logs are taken of all variables before estimating VAR. So, the cumulative response is the percent change in the variable

with an aggregate demand shock, Black employment responds much more. With long-run growth, however, the type that might come from productivity shocks, that sensitivity is nonexistent for the median labor market. In some areas, Black workers are more sensitive to macro fluctuations and thus will benefit more when there is an economic boom holds true. But, for the bottom 25% quantile, the sensitivity is revered: Black workers benefit relatively less than White workers. This serves as a first example of why knowing the difference between the type of fluctuation is important with regard to labor market inequality. Not all growth is equal and knowing whether Black workers will benefit more or be left behind when there is output growth is important for implementing effective policy.

Figure 2: Cumulative Response of Employment Gap to Idiosyncratic Shocks

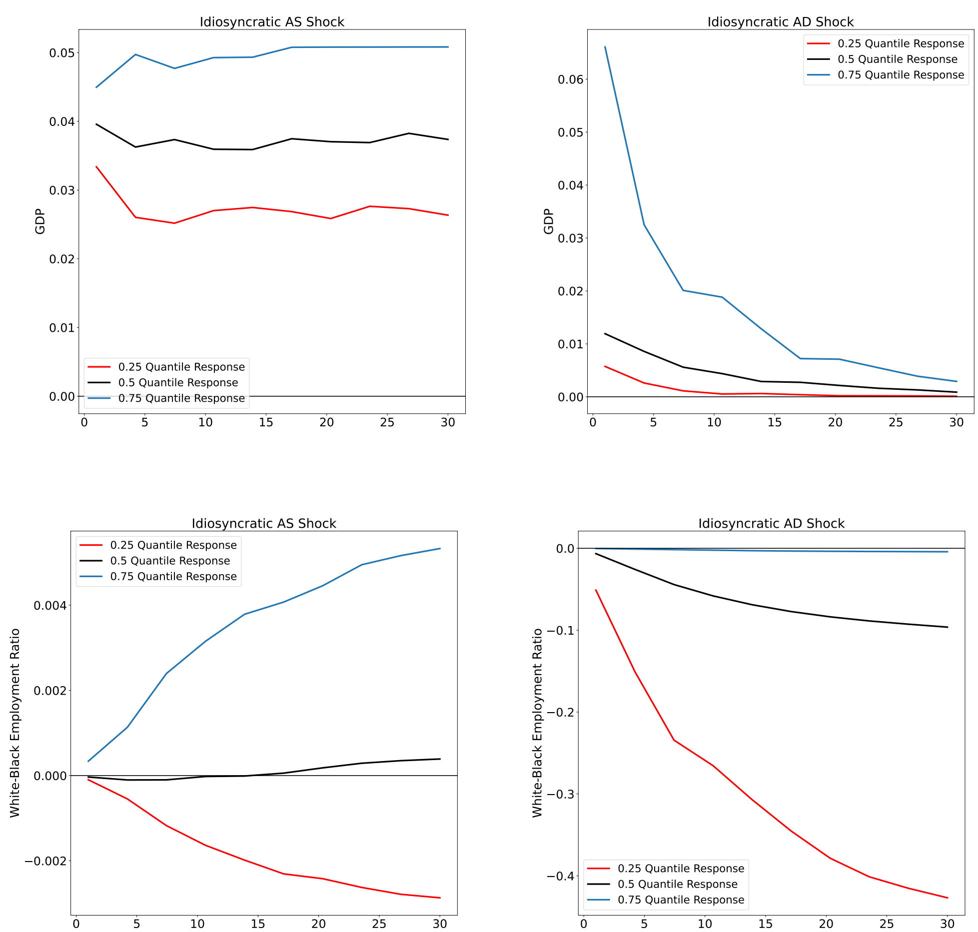
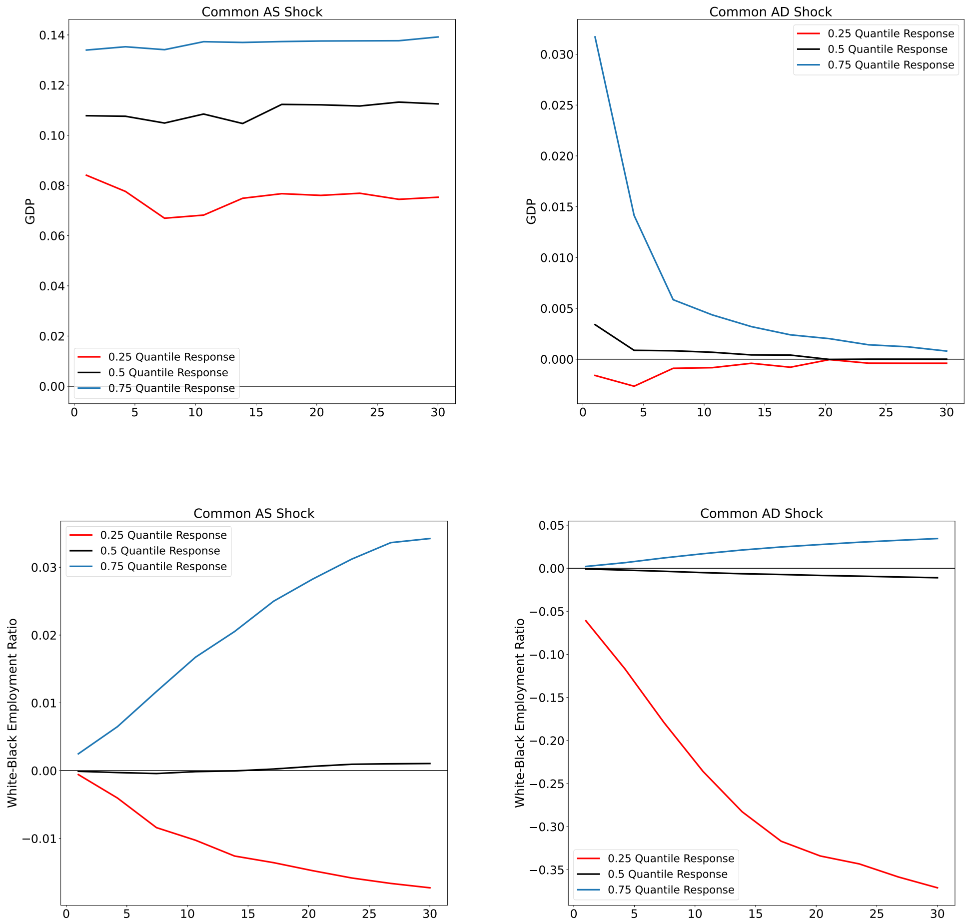


Figure 3: Cumulative Response of Employment Gap to Common Shocks



Second Stage Analysis — What explains Black employment's differing sensitivity to short-run versus long-run growth? To answer this, I will conduct a second stage analysis using step 30 of the impulse response to an idiosyncratic supply and demand shock (since the heterogeneity of interest is at the end of the response). Table 2 reveals that the most significant margins for explaining the heterogeneity is the share of workers with Bachelor's degrees, share of primary sector employment, and geographic location.

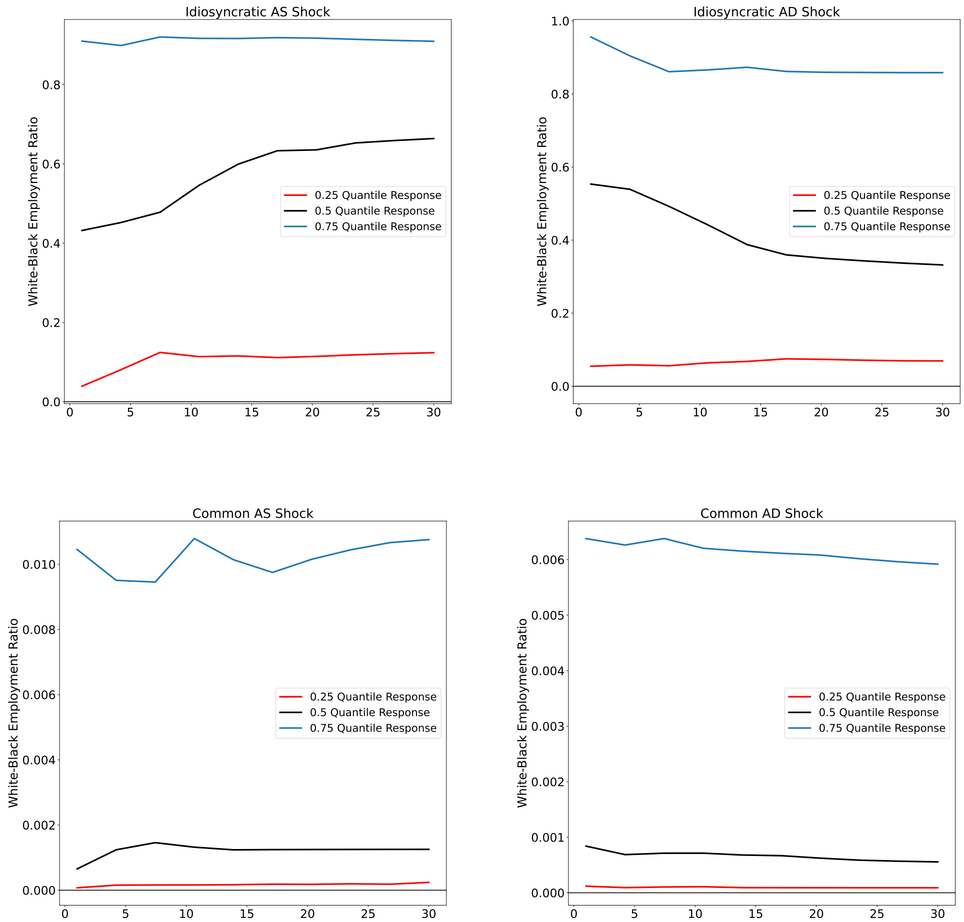
Table 2: Second Stage Analysis of White-Black Employment Ratio

| White-Black Employment Gap | (1) AS | (2) AD |
|---|---|---|
| Bachelor's Share | -0.0150** | 0.0899*** |
| | (0.00567) | (0.0320) |
| Primary Sector Share | -0.136** | 0.656* |
| | (0.0635) | (0.358) |
| Secondary Sector Share | -0.0351 | 0.116 |
| | (0.0289) | (0.163) |
| Tertiary Sector Share | -0.0108 | 0.0689 |
| | (0.00962) | (0.0542) |
| Labor Market Tightness | -0.000947 | -0.00507 |
| | (0.00365) | (0.0206) |
| South | -0.00141** | 0.00544 |
| | (0.000600) | (0.00338) |
| Midwest | -2.68e-05 | 0.00249 |
| | (0.000570) | (0.00322) |
| Northeast | -0.000503 | -0.00148 |
| | (0.000582) | (0.00328) |
| Constant | 0.00859** | -0.0455* |
| | (0.00403) | (0.0227) |
| Observations | 60 | 60 |
| R-squared | 0.278 | 0.226 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The coefficient on bachelor's share switches from negative to positive going from an aggregate supply to a demand shock. With an aggregate supply shock, a higher share of workers with bachelor degrees is associated with relatively better improvement for Black employment. With an aggregate demand shock, however, a higher share of bachelor's degree is associated with Black workers performing relatively worse than White workers (since the ratio is increasing). A similar situation is occurring with the share of employment in the primary sector. With long-run growth, a higher share of employment in the primary sector is associated with Black employment improving relatively more than White employment but the opposite is true when it comes to aggregate demand shocks. An economic intuition explaining this pattern is not immediately obvious. On the one hand, since aggregate demand shocks are transitory periods of growth, it could make sense that labor markets with a higher share of bachelor degrees see Black workers benefit relatively less as the types of jobs created in more educated labor markets may not be the best match for Black workers who, on average, tend to have less skills than White workers. A similar story can be told about primary sector share. Since White workers tend to be employed more in the primary sector than Black workers, a transitory economic boom is likely to benefit White workers in regions with higher employment share in the primary sector. But what explains Bachelor's Share and Primary Sector Share becoming associated with relative improvements in Black employment when as aggregate supply shock happens instead of an aggregate demand shock? The jobs created in these areas from long-run growth could be better matches for Black workers than the ones created in these areas as a result of an aggregate demand shock. However, the answer is not obvious. What is clear, however, is that fluctuations in local employment differentials is almost entirely driven by idiosyncratic shocks as the variance decomposition below shows. Nearly all the variance in the White-Black employment ratio is explained by idiosyncratic aggregate demand and supply shocks. So while the effect of economic fluctuations like oil or monetary policy are still relevant questions (and will be explored in this paper), the ultimate path to closing these gaps lies at the local level.

Figure 4: Variance Decomposition of Black-White Employment Gap



Labor Market Flows — The next labor market indicator will be the gap between Black and White flows into/out of persistent unemployment. More specifically, I construct the separation rate into a non-employment spell as well as the hiring rate from a non-employment spell. The J2J gives counts for the number of such hires and separations while the QWI gives total employment levels. Normalizing by total employment count will be important for making sensible comparisons as we did earlier with the actual job losing and job finding hazard rates. It's still worth mentioning that the goal of this indicator is to better approximate unemployment flows. Our persistent separation rate is likely to better capture inflows to unemployment as the numerator won't have much turnover present. Our persistent hiring rate should also do a better job as it will only count hires who had a period of nonemployment beforehand. So while not perfect, these two indicators should better approximate unemployment flows separate from turnover. To make relative comparisons between the Black and White workers, I subtract the Black persistent rate from the White rate:[14]

$$\begin{aligned}\text{Persistent Hiring/Separation Gap} = \quad & \text{White Persistent Hiring/Separation Rate} \;- \\ & \quad\text{Black Persistent Hiring/Separation Rate}\end{aligned}$$

Figures 5 and 6 estimate the same structural panel VAR as before but using the persistent hiring gap as an indicator. Because of the nature of the J2J, the number of time periods drops to 88. However, this should be enough given the good small sample size performance of Pedroni (2013).

What's clear across both common and idiosyncratic shocks is that aggregate supply shocks almost always bring in relatively more Black individuals from nonemployment into the workforce than White workers (since the gap is declining). With aggregate demand shocks, however, there is considerable heterogeneity. The median response for both common and idiosyncratic aggregate demand shocks is close to zero—meaning that on the whole, the relative flows from nonemployment between the two races doesn't change much. There are some regions where Black persistent hiring performs relatively better than White persistent hiring but the effect is not large. What might explain the distribu-

[14] I don't use a ratio as the numbers are small

tional consequences of aggregate supply versus aggregate demand shocks on flow from nonemployment? Our story about marginally attached workers and the real wage certainly fits. Black workers are going to operate on the margins of the employment/labor force more so than White workers. With a long-run growth fluctuation like aggregate supply, the real wage may be increasing and thus incentivising marginally attached workers to enter employment. There may also be better matches between the jobs created from aggregate supply shocks and Black workers. As for our measure of separation into a period of nonemployment, figure 7 tries to test the "first-fired" hypothesis—the idea that Black workers are the first fired in when a recession hits—by testing how our measure of the separation rate responds to a negative aggregate demand and supply shock. And while in the upper quantile response, the black separation rate is increasing, the median and lower response quantile see the separation rate decline—suggesting that our measure is not well approximating unemployment flows.

All in all, short-run transitory versus long-run growth has different implications for White-Black employment differentials across local labor markets. Flows from nonemployment for Black workers rise relatively more than flows for White workers in response to aggregate supply shocks but not in response to aggregate demand shocks. However, Black employment as a whole is more sensitive to aggregate demand fluctuations than White employment. In all cases, the primary driver of fluctuations in labor market inequality are idiosyncratic shocks so although the concern with national shocks and inequality is certainly relevant (and will occupy the rest of this paper), unemployment differentials are ultimately a local problem that require a local solution.

Figure 5: Cumulative Response of Persistent Hiring Gap to Idiosyncratic Shocks

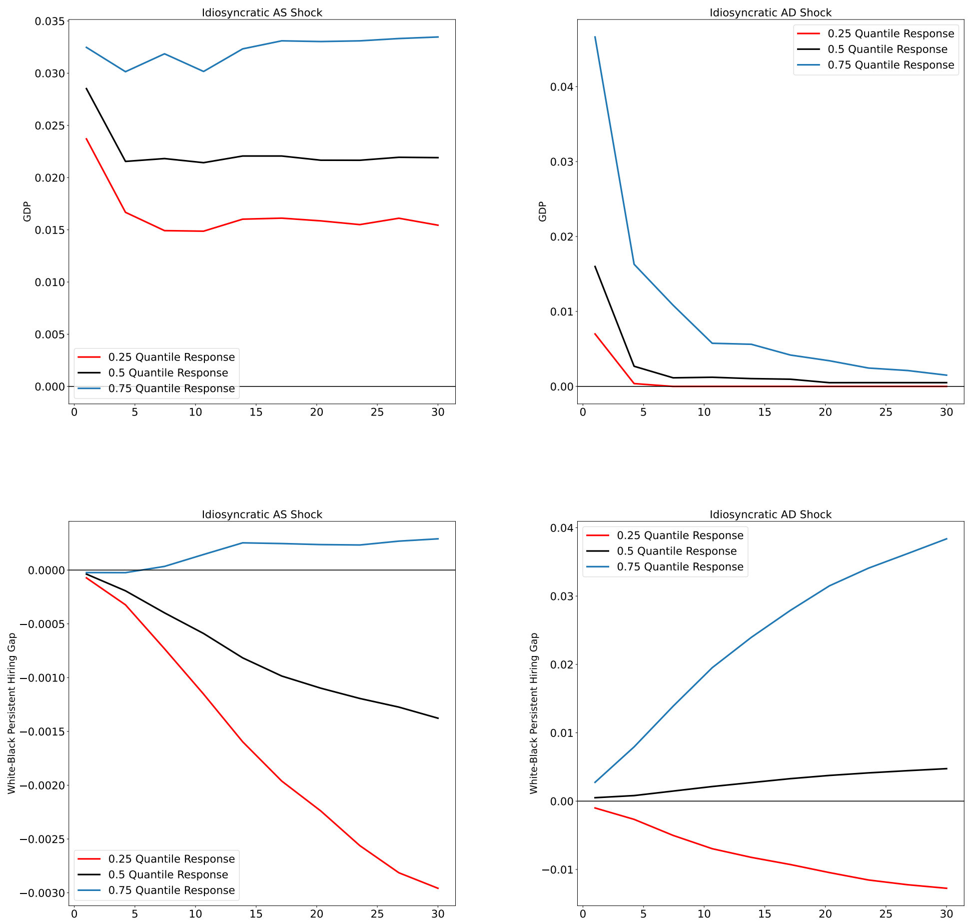


Figure 6: Cumulative Response of Persistent Hiring Gap to Common Shocks

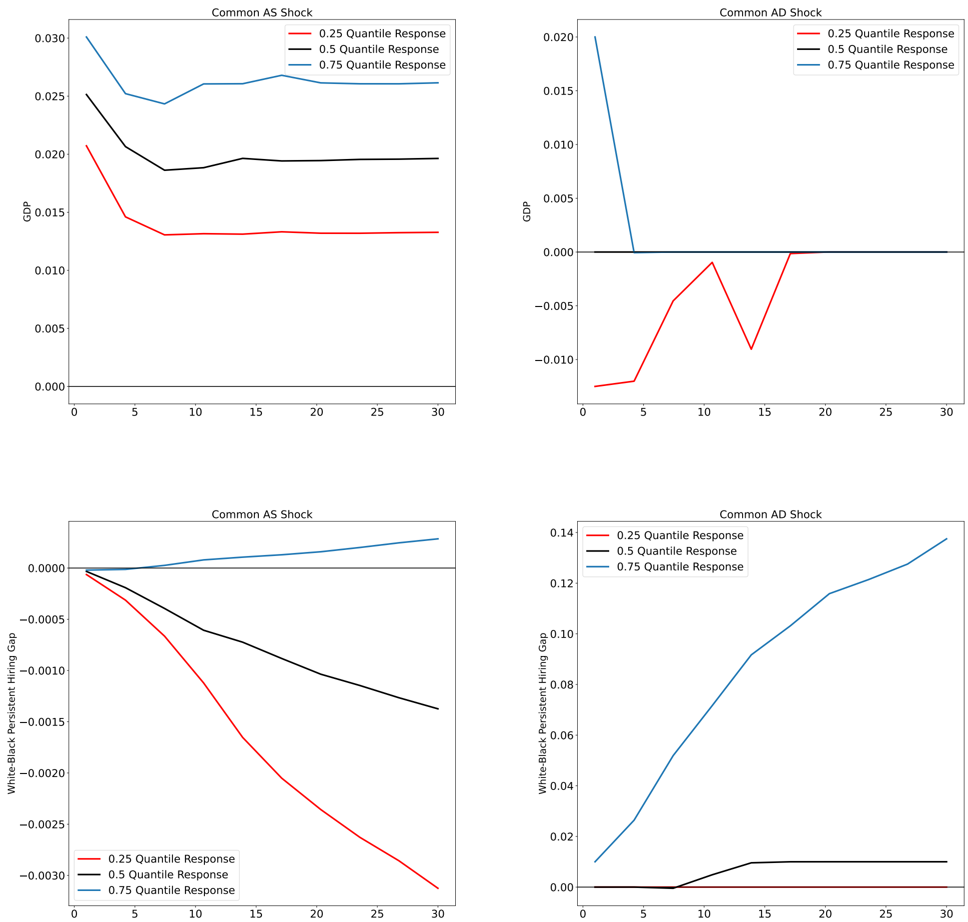
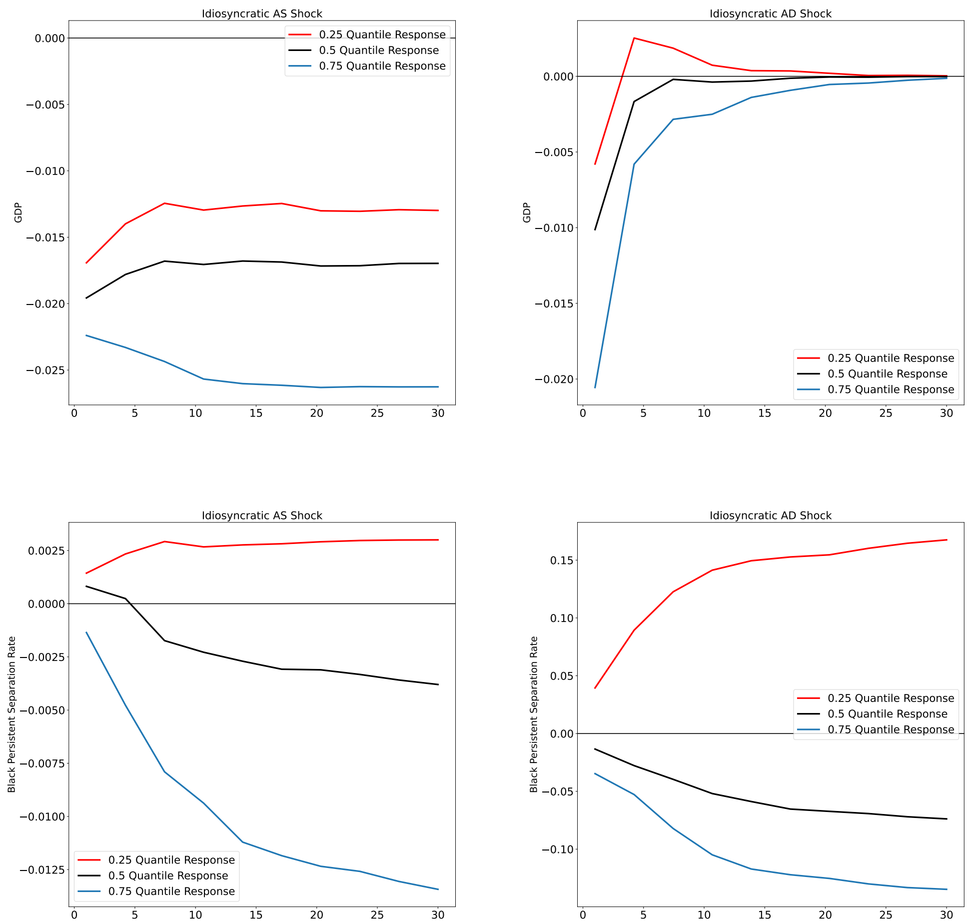


Figure 7: Cumulative Response of Black Persistent Separation Rate to Idiosyncratic Shocks

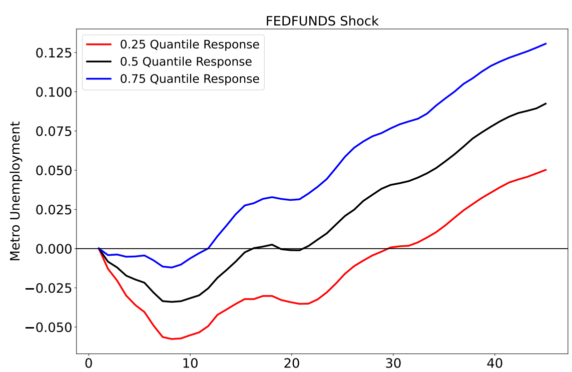


### B. Policy Fluctuations

The next category of fluctuations considered are those set by policymakers, specifically monetary policy.

Geographic Unemployment Gaps (Monthly Specification) — I will first use the monthly specification in an attempt to uncover any regional heterogeneity in how labor markets respond to federal funds rate shocks, and thus explore how geographical unemployment gaps narrow/widen. Figure 8 plots the quantiles of the cumulative response of metropolitan/micropolitan unemployment rates to a positive federal funds shock while figure A4 plots the entire system.[15] At first, unanticipated innovations in the federal funds rate does not lead unemployment rates to rise but instead fall briefly. But by the 40th[16] month, the brief decline is reversed as the the median labor market sees an overall 7.5% increase in their unemployment rate from the first quarter. As expected, labor markets see their unemployment rates rise to increases in the federal funds rate but there is a non-trivial amount of heterogeneity in terms of how sensitive a labor market is to interest rate changes.

Figure 8: Cumulative Response of Unemployment to Federal Funds Shock




*Notes:* FEDFUNDS shock is normalized to cause a 25% increase in the federal funds rate

To explain this, I will perform another second stage analysis (3) by regressing

[15] responses are not normalized in the full system
[16] responses level off after 60+ months but are not graphed to save space

the long-run unemployment response[17] against our set of static characteristics. The most significant mediators of federal funds shocks are the population share of bachelor degrees and the employment share of the primary and secondary sectors. A higher share of bachelor degrees lessens the rise in the unemployment rate following a federal funds shock as its coefficient is negative. The blunting effect of education makes sense as higher skilled jobs are less likely to be cyclically sensitive to interest rates. A higher employment share in both the primary and secondary sector is associated with a larger response in unemployment—falling in line with a wide literature on interest rate sensitivity of industries involved in manufacturing and extraction (Wagan et al., 2018). Lastly, the finding that higher labor market tightness is associated with higher unemployment sensitivity may seem a bit surprising as tight labor markets are usually good for employment prospects. However, remember that this is a linear VAR so if we consider the opposite situation where a negative shock to the federal funds occurs, it makes sense that the coefficient here is positive. In a tighter labor market, the effect of a drop in the federal funds rate on employment would be enhanced by the stronger ability of individuals to find jobs—meaning that the coefficient would negative. Here, where the shock is positive, it's just flipped.

[17] step 40 in the cumulative impulse response

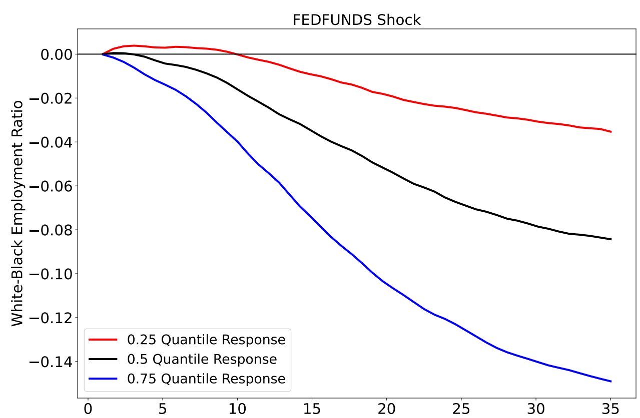
Table 3: Second Stage Analysis of Geographic Unemployment Responses

| | (1) |
|---|---|
| Unemployment Rate Response | FedFunds |
| Bachelor's Share | -0.0541*** |
| | (0.0121) |
| Primary Sector Share | 0.180* |
| | (0.0985) |
| Secondary Share | 0.102*** |
| | (0.0332) |
| Tertiary Sector Share | 0.0949 |
| | (0.0662) |
| Labor Market Tightness | 0.0137** |
| | (0.00600) |
| South | -0.00218* |
| | (0.00122) |
| Midwest | -0.00206 |
| | (0.00182) |
| Northeast | -0.00181 |
| | (0.00125) |
| Constant | -0.000150 |
| | (0.0103) |
| Observations | 888 |
| R-squared | 0.033 |

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

White-Black Employment Gap (Quarterly Specification) — Often, a question that has been posed in the monetary policy and inequality literature is whether expansionary monetary policy can close racial unemployment gaps. To answer this, Figure 9 plots the response of the White-Black Employment Ratio to a negative shock in the federal funds rate. Since the ratio is declining for all quantile responses, it's easy to see why many think that monetary policy can boost Black employment relatively more than White employment, e.g., Bergman, Matsa and Weber (2022). However, this should be expected given what we already know about the sensitivity of Black employment to aggregate demand fluctuations. Black employment growth nearly always outpaced White employment growth when it came to short-run fluctuations, such as a drop in interest rates. So, the finding that Black employment being more sensitive to monetary policy is most likely a byproduct Black workers' already being sensitive to macro fluctuations. It's important to remember that our VAR is linear. So, even if expansionary monetary policy is found to close these employment gaps, as I do here, as soon as an opposite shock of the same size happens, those benefits wash away. All in all, while there is evidence of distributional consequences of monetary policy fluctuations on both the geographic and racial level, the distributional consequences across geography appear to be more tied to the tools of monetary policy specifically, e.g., interest rates, rather than preexisting sensitivities to the macro-economy.

Figure 9: Cumulative Response of White-Black Employment Ratio to FF Shock




*Notes:* FEDFUNDS shock is normalized to cause a 25% decrease in the federal funds rate

### C. Global Fluctuations

The next category of fluctuations have a global origin: oil prices and exchange rates. There is a literature on the implications of both of these variables on inequality, especially at the aggregate level, but few have taken a heterogeneous panel approach. So, as with the earlier categories of fluctuations, the goal here is uncover any heterogeneity in the impact of either global fluctuation on labor market inequality. More specifically, I will be focusing on the geographical margin of labor market inequality since that is likely to be the primary distributional factor.

Oil Prices — The reason for going to the trouble of not just disentangling oil price shocks from economic activity but further disentangling them into oil-specific supply, oil-demand specific, and global commodity demand-specific forces is that all three may lead to the same rise in the price of oil but (as Kilian (2009) finds) each are going to differ in their effect on economic growth and thus labor market inequality. The steps Kilian took to decompose movements in oil prices were carefully followed when I adapted his identification scheme to a block structural panel VAR. Figure A1 plots the full system from 1974m1 to 2022m12. However, as a robustness check, I also estimated the system using the same timeline in Kilian's paper. I did this for two reasons. When the model was estimated over the complete timeline, a slight difference arose between it and Kilian's original findings: an oil supply shock that increases crude oil production lead to a decline in global activity. Now, there are a few explanations. Kilian's original paper used a older version of the index for global activity that has since been corrected. Another is that nearly 2 decades have passed and the dynamic relationships could easily have changed. So, to ensure my estimation was correct, I estimated the system using the same timeline as Kilian and got the similar results qualitatively to his paper, i.e., a positive oil supply shock lead to an increase in global activity. All other responses were qualitatively[18] similar also. Figure A2 is my replication of Kilian while figure A1 is the estimation done at the complete timeline. Nonetheless, since my replication of Kilian's timeline aligned with the original paper, it's reasonable to think that the relationship between oil supply shocks and global activity has changed over the last 2 decades. The reason behind that, however,

[18] I say qualitatively because lag choices can affect precise numerical estimates. The overall shape matched between my replication and the original paper

is beyond the scope of this paper.

Below are the percentile responses of metropolitan/metropolitan unemployment rates to each structural shock. Each shock is normalized to cause roughly a 10% increase in the price of oil. As expected the consequences of a oil price shock depend on the underlying cause that movement. An oil supply shock that causes a 10% increase in the price of oil doesn't change unemployment rates on average. But, the 25% and 75% response indicates that oil supply shocks can have both positive and negative effects on regional unemployment rates. Price increases driven by global demand for commodities initially lower unemployment rates but this is eventually reversed after 20-30 months. This is consistent with Kilian's findings that global aggregate demand shocks initially provide a boost to US output as the increased global demand offsets the higher oil price. However, eventually, that "stimulus dies out" (Kilian, 2009) and the adverse effect of the higher commodity prices triggered by the initial shock leads to a delayed recession, as evidenced by the uptick in unemployment rates after 30 months. Oil-specific demand unambiguously causes the unemployment rate to fall for local labor markets. However, it should noted from the that estimated effect of each shock on the percent change in unemployment is quite small. No shock causes more than a 2% change in the unemployment rate after a 10% increase in the price of oil. The fact that the strongest increase in unemployment doesn't necessarily even come from an oil price increase itself but rather the delayed recession that happens after a global commodity demand driven increase in the price of oil suggests that oil prices themselves may not be what affects unemployment outcomes but rather the spillover effect it has on the global economy. Nonetheless, it is worth explaining why these different shocks may differentially affect unemployment rates across labor markets via another second stage analysis in table 4. Perhaps as expected, the most consistent mediator of how much any type of oil shock will affect local unemployment is the employment share of the primary and secondary sectors, which makes perfect sense as these are industries involved in the extraction of raw materials and production of final goods.

Figure 10: Oil and Unemployment Dynamics

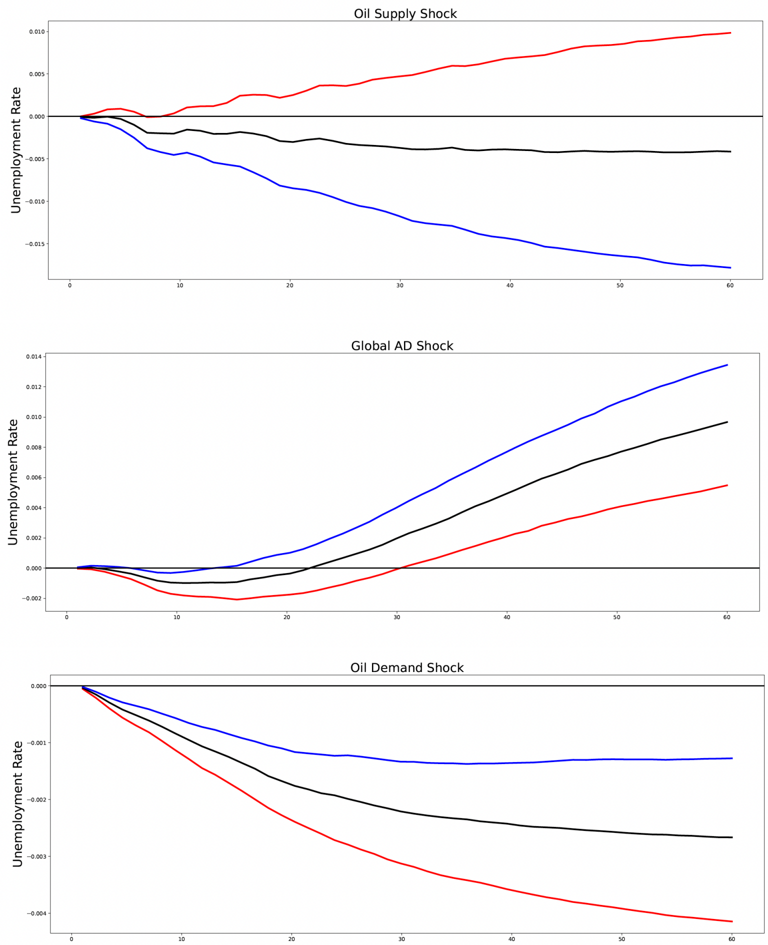


Table 4: Second Stage Analysis of Oil

| VARIABLES | (Oil Supply) Medium-run | (Oil Supply) Long-run | (Global AD) Medium-run | (Global AD) Long-run | (Oil Demand) Medium-run | (Oil Demand) Long-run |
|---|---|---|---|---|---|---|
| Bachelor's Share | -0.0387* | -0.618*** | -0.000417 | 0.00428*** | -0.0191*** | -0.0304 |
| | (0.0214) | (0.0992) | (0.000254) | (0.000875) | (0.00395) | (0.0200) |
| Primary Sector Share | 0.630*** | 2.149*** | -0.00513*** | -0.0133*** | -0.120*** | -0.961*** |
| | (0.125) | (0.581) | (0.00149) | (0.00512) | (0.0231) | (0.117) |
| Secondary Share | 0.0173 | -0.826*** | -0.00368*** | 0.0227*** | -0.0819*** | -0.0954* |
| | (0.0592) | (0.274) | (0.000701) | (0.00241) | (0.0109) | (0.0553) |
| Tertiary Sector Share | 0.0588** | 0.0810 | -0.00108*** | 0.00505*** | -0.0257*** | -0.0729*** |
| | (0.0259) | (0.120) | (0.000307) | (0.00106) | (0.00478) | (0.0243) |
| Labor Market Tightness | 0.0360*** | 0.160*** | -0.000392*** | -0.00124*** | -0.0126*** | -0.0564*** |
| | (0.0107) | (0.0496) | (0.000127) | (0.000438) | (0.00198) | (0.0100) |
| South | -0.00401* | -0.0215** | 4.63e-05* | 0.000207** | 0.00156*** | 0.00691*** |
| | (0.00220) | (0.0102) | (2.61e-05) | (9.00e-05) | (0.000407) | (0.00206) |
| Midwest | 0.00488 | 0.00146 | 3.48e-05 | -0.000165 | -0.000330 | -0.00239 |
| | (0.00329) | (0.0152) | (3.90e-05) | (0.000134) | (0.000607) | (0.00308) |
| Northeast | 0.000949 | 0.00180 | 0.000101*** | 0.000204** | -9.60e-05 | 0.00250 |
| | (0.00225) | (0.0104) | (2.66e-05) | (9.17e-05) | (0.000414) | (0.00210) |
| Constant | -0.00704 | 0.111** | 0.000306*** | -0.00125*** | 0.00758*** | 0.0171* |
| | (0.00952) | (0.0440) | (0.000113) | (0.000388) | (0.00175) | (0.00890) |
| Observations | 888 | 888 | 888 | 888 | 888 | 888 |
| R-squared | 0.068 | 0.109 | 0.056 | 0.195 | 0.216 | 0.146 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Exchange Rates — The final source of economic fluctuation that will be studied for its effect on labor market inequality is the US real effective exchange rate. Figure A3 plots the unscaled responses of the entire exchange rate system. However, below is the cumulative response of metropolitan unemployment rates to a shock in the US real effective narrow exchange rate (RNEER) that causes it rise by 30%. For labor markets as a whole, a unanticipated innovation in RNEER of 30% leads to a modest increase in the median labor market's unemployment rate. A 30% increase may be too large, however, to be a relevant thought experiment. But even if it is scaled down by a factor of 3, the upper 75% of metropolitan areas would still see an increase in their unemployment rate. This illustrates the necessity of taking a heterogeneous panel approach to studying the effect of economic shocks on inequality. If this analysis had been done at the national level, the effect would have most likely averaged out. But by disaggregating down to the local labor market, we can see that the brunt of unanticipated innovations in exchange rates are only felt by a portion of local labor markets.

Second Stage Analysis — What explains this greater sensitivity? Table 5 performs another 2nd stage analysis to explain why some labor markets are more sensitive to exchange rate fluctuations. The most significant explanation of sensitivity to exchange rate shocks is the secondary sector's employment share, which makes sense as that is the part of the economy involved in the production of final goods and thus will be some of the first to feel the effects of a dollar appreciation. A higher share of employment in the secondary share is associated with a larger increase in the unemployment rate following a positive exchange rate shock.

Figure 11: Cumulative Response of MSA Unemployment to Exchange Rate Shock

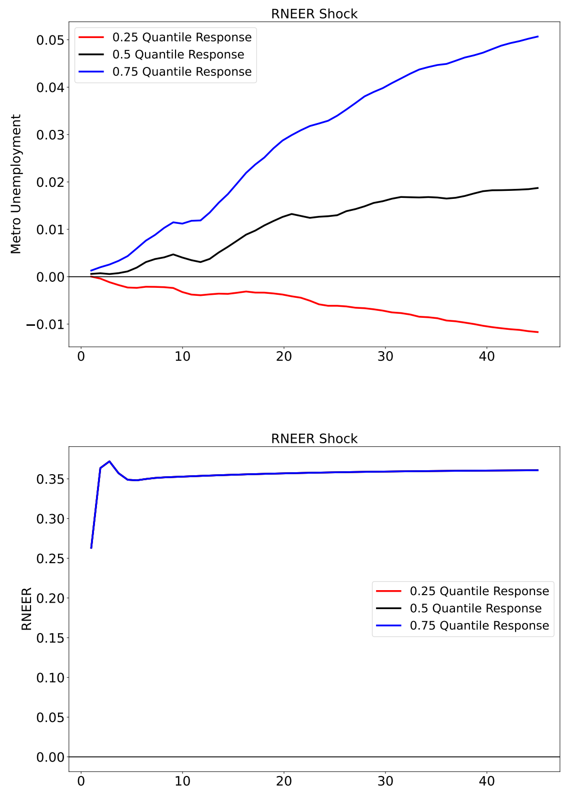


Table 5: Second Stage Analysis of Exchange Rate Shocks

| VARIABLES | (1)<br>Long-Run |
|---|---|
| Bachelor's Share | -0.0766 |
| | (0.0491) |
| Primary Sector Share | 0.367 |
| | (0.288) |
| Secondary Sector Share | 0.346** |
| | (0.136) |
| Tertiary Sector Share | -0.0275 |
| | (0.0595) |
| Labor Market Tightness | 0.0518** |
| | (0.0246) |
| South | -0.00910* |
| | (0.00505) |
| Midwest | 0.00987 |
| | (0.00754) |
| Northeast | 0.00161 |
| | (0.00515) |
| Constant | 0.0380* |
| | (0.0218) |
| Observations | 888 |
| R-squared | 0.016 0.036 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

## IV. Conclusion

Whatever the economic fluctuation of interest is—monetary policy, oil prices, spending shocks, global activity—if you want a complete picture of its implications for inequality, not only do you need to look at gaps across race but you also need to account for gaps across geography. This paper has explored some of the prototypical shocks considered within the AD-AS framework and found that nearly all have heterogeneous impacts on inequality that would have likely have been washed out in an aggregate level analysis. Our heterogeneous panel approach allowed us to see the differing implications for White-Black differentials in response to transitory versus long-run growth. The classical story of greater Black sensitivity to macro fluctuations is true with regard to demand-side shocks but for supply-side, that sensitivity is reversed for many labor markets. As for policy fluctuations, this approach revealed the geographic differences that can mediate or enlarge the effect of interest rate shocks. It also revealed that not all oil price shocks cause unemployment to rise. The only source of oil price fluctuation of real significance are those from global demand for commodities, as shocks originating here have much larger effects on the global business cycle and thus local unemployment rates relative to oil-specific shocks. This paper's approach also illustrated even though RNEER fluctuations may have a zero effect on local unemployment rates for the median labor market, for a nontrivial number of labor markets, even modest positive innovations cause unemployment rates to rise. None of these findings would have been possible with an aggregate analysis—further highlighting the fact the labor market inequality is a local problem and it must be studied as such.

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## Graphs for each System

Figure A1: Full Oil System (1974m1 - 2022m12)

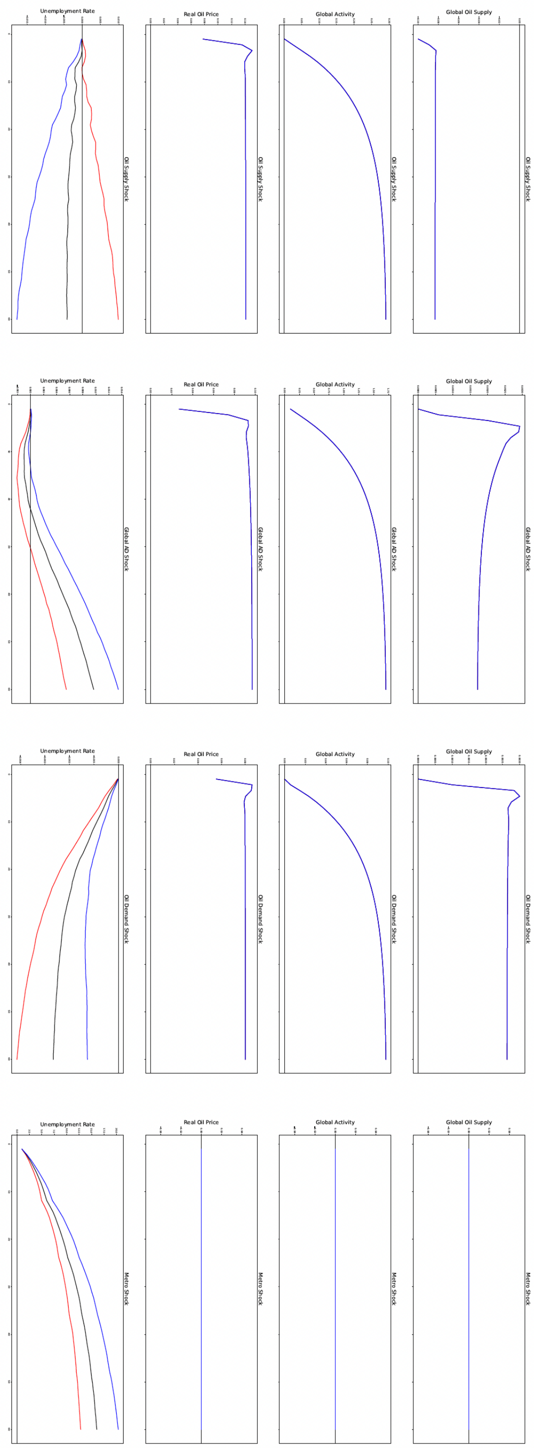

Figure A2: Kilian Check (1974m1 - 2006m12)

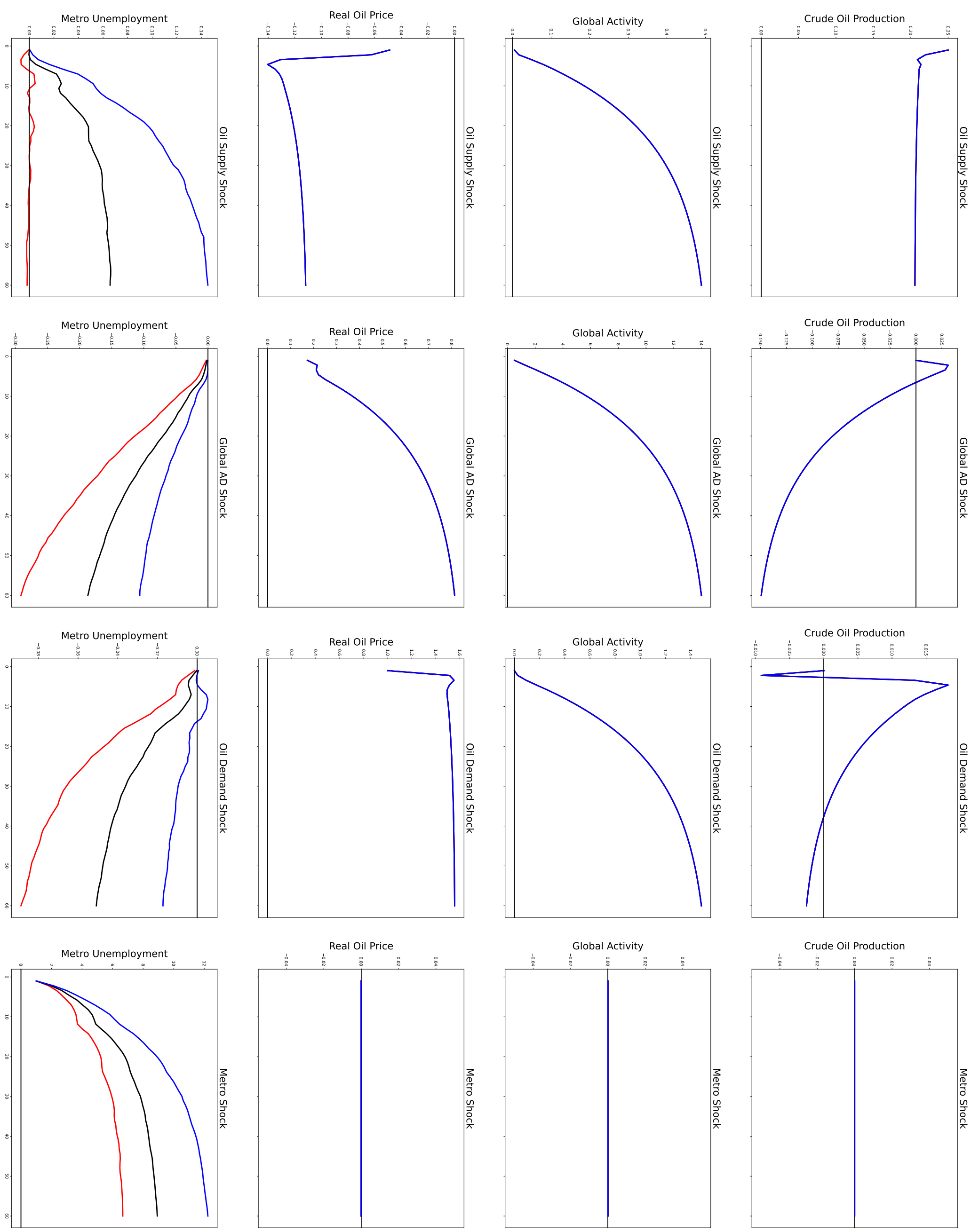

Figure A3: Exchange Rate System (1990m1 - 2022m12)

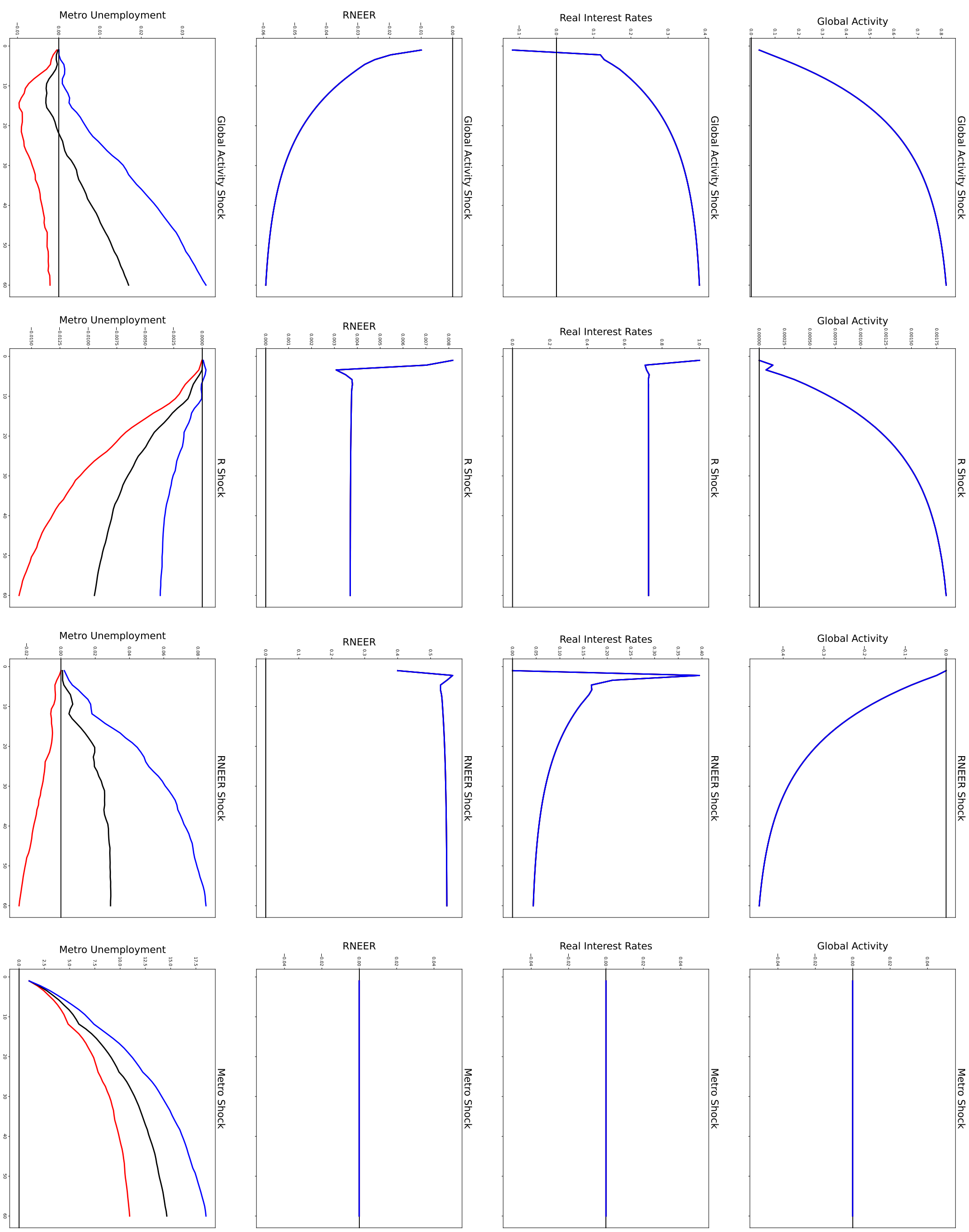

Figure A4: Monthly Monetary VAR (1986m1 - 2022m12)

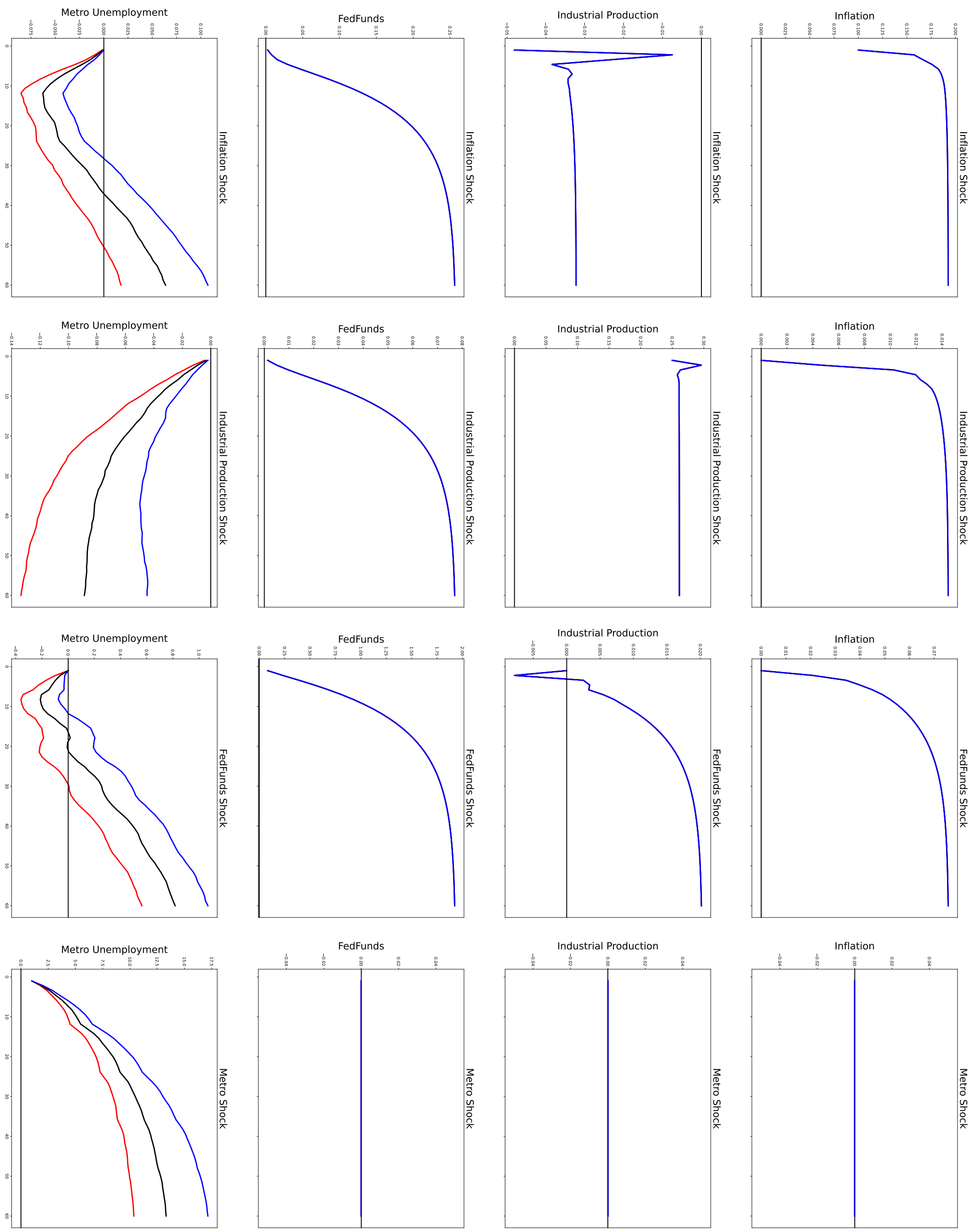

Figure A5: Quarterly Monetary VAR (1986q1 - 2022q4)