Extended Abstract: Estimating Distributional Responses to Macroeconomic Shocks

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Preliminary: Comments Welcome

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A growing literature seeks to understand how inequality changes over the business cycle. As documented by Heathcote et al. [2010], various measures of income dispersion appear to be countercyclical. Our goal is to study the cyclical dynamics of the earnings distribution, but we want to do more than summarize the distribution, conditional on the economy being in expansion or recession. For instance, one might think that dispersion looks different in an expansion caused by a technology shock, compared to an expansion caused by a monetary shock. Likewise, one might think that a given shock has different effects on different conditional distributions, such as the earnings distribution for college graduates and the earnings distribution for high school graduates.

We will develop tools for measuring how the distribution responds to identified macroeconomic shocks. Our strategy will be to combine tools from structural time series with tools from non-parametric Bayesian statistics. Consider a distributional model of the following form:

$$y_{i,t} \mid \mathbf{z}_{i,t} \overset{\text{i.i.d.}}{\sim} f\left(\cdot \mid \mathbf{z}_{i,t}\right). \tag{1}$$

In the above, $y_{i,t}$ is the a measure of person i's earnings at date t. The vector $\mathbf{z}_{i,t}$ contains covariates that describe person i at date t. The function $f\left(y \mid \mathbf{z}\right)$ is the density of the conditional distribution of earnings, given covariates. We will partition the covariates as $\mathbf{z}_{i,t} = \left(\mathbf{a}_t', \mathbf{x}_{i,t}'\right)'$, where $\mathbf{a}_t$ is a vector of macroeconomic aggregates that affect all workers in the economy at date t, and $\mathbf{x}_{i,t}$ is a vector of individual i's personal characteristics. The

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micro-level data we'll be using come from the Current Population Survey. This provides us with a large sample at a sufficiently high frequency to examine business-cycle fluctuations, rather than the annual sampling in some other datasets (e.g., Guvenen et al. [2014]).

The first step is estimating the function $f(y \mid \mathbf{z})$ non-parametrically in order to provide a flexible statistical description of inequality, conditional on workers' individual characteristics and the state of the economy. Here, we utilize the dependent Dirichlet process mixture (DPM) model with a Gaussian kernel and base measure, along the lines of Escobar and West [1995] and MacEachern [1999]. This is equivalent to treating $y_{i,t}$ as a mixture of infinitely many normal distributions with random mean and variance. Computationally, this method of density estimation has a conditionally conjugate form, which is very tractable. Taking a Bayesian approach is also advantageous for dealing with the curse of dimensionality. We want to estimate the distribution of wages flexibly while conditioning on a reasonably large number of variables. The dependent DPM allows us to adopt a prior that's centered on a normal linear regression, while providing enough flexibility to capture nonlinear dependencies across many covariates.

The second step is characterize the dynamics of macroeconomic aggregates in response to identified shocks. Here, we draw on the structural VAR literature. Ramey [2016] provides a thorough summary of identification strategies for detecting various macroeconomic disturbances, such as technology shocks, fiscal shocks, and monetary shocks. We will fit a Bayesian VAR to the aggregate data, and using the time-series model, we'll identify how $\mathbf{a}_t$ responds to a shock (e.g., a total-factor productivity shock). By taking the impulse response of $\mathbf{a}_t$ implied by the time-series model and "feeding it through" the function $f(y \mid \mathbf{z})$, we'll see how the distribution of earnings moves in response to the shock. Our strategy will be semi-structural, in the sense that we're identifying interpretable macroeconomic shocks, but not imposing all of the restrictions implied by a fully specified general equilibrium model.

References

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