

# Xiaoxue (Shirley) Song

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## JOB MARKET CONTACT

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## OFFICE CONTACT

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## EDUCATION

**Indiana University, Bloomington, IN, U.S.**

*Ph.D.* Candidate in Economics (STEM)

May 2022 (Anticipated)

**Fields:** Applied Econometrics, Macroeconomics, Labor Economics

*M.A.* Economics

Dec. 2018

**University of Michigan, Ann Arbor, MI, U.S.**

*M.A.* Applied Economics

May 2014

**Dongbei University of Finance and Economics, Dalian, China**

*B.A.* Economics

June 2011

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## WORKING PAPERS

**Does Age Matter for the Labor Market Effects of Technological Progress?**

*Job Market Paper*

· **Abstract:** A central question in macroeconomics is: how do labor market outcomes change in response to technological progress? We broaden this question by asking if there are age-specific effects, e.g., are young workers affected in the same way as people close to retirement? We explicitly model the employment to population ratio as a function of age and use mixed autoregression to (i) directly analyze the dynamics of this function, and (ii) study the effects of changes in technology via long-run restrictions on the impact of technology shocks.

The average impact response across ages is negative, which is in line with the aggregate employment response in Galí (1999). However, the responses of the young and the old are much more negative than the prime-age response, and the response of the young is three times lower than that of the old. The contribution from technology shocks decreases by age relative to non-technology shocks. For young and prime-age workers, about 40% of variations in employment can be explained by technology shocks, while non-technology shocks explain about 60%. However, non-technology shocks explain more than 80% of variations in employment for workers of ages 54-65.

**Beyond the Average: Investigate the Cyclical Fluctuations of Participation at the Disaggregated Level.**

*Work in Progress*

· In this paper, we study the cyclical fluctuations of the participation of the population from ages 16 to 65 as a curve in the functional structural vector-autoregression model. We extend the functional structural vector-autoregression model in Chang, Kim and Park (2019) to apply sign restrictions to identify four structural shocks, demand shocks, technology shocks, labor supply shocks, and wage bargaining shocks. We find the participation of 16-65 years old responds heterogeneously to the four shocks in both directions and magnitude. Besides, we find in the short run and medium run, demand and technology shocks are more important in driving the fluctuations of the young's participation, but wage bargaining shocks are more important for the prime-age and the old's participation. In the long run, labor supply shocks are the main driving forces of the participation variations of all ages from 16-65.

# The Role of Monetary Policy in Job Polarization and Jobless Recoveries: A Mixed Vector Autoregression Approach.

*Work in Progress*

- This paper looks at the employment heterogeneity across different occupations, as well as the role of monetary policy in the context of job polarization and jobless recoveries. Jobless recoveries happened after 1991, 2001, and 2009 recessions, when employment continued to contract although the real GDP had been expanding. Job polarization is referring to the phenomenon that the employment share of non-routine cognitive (high-skill) and non-routine manual (low-skill) jobs were increasing, while routine jobs were decreasing after the 1990s. The heterogeneous task profile of different occupations plays an important role in analyzing the effect of monetary policy on jobless recoveries. For example, a decrease in interest rates will incentivize firms to use cheaper capital, increasing the likelihood that occupations with routine tasks will be replaced by machines or robots. In this paper, I will use the externally identified money policy shocks to see how they will affect the employment of occupations with different task profiles within the framework of mixture autoregression.

## WORKING EXPERIENCE

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### Inter-university Consortium for Political and Social Research

*Mar. 2014-May. 2015*

*Research Assistant*

- Exacted and presented data usage metrics (popular datasets, data types, number of unique users, data user profiles, etc.) from data repositories access information dataset; provided valuable ways to evaluate data usage for NICHD funding. <https://www.icpsr.umich.edu/web/pages/DSDR/metrics.html>

## HONORS AND CONFERENCES

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Crawford Fellowship

*Fall 2019*

Department Conference Funding Award

*Fall 2019*

Daniel J. Duesterberg Award from Department of Economics at IU

*Fall 2018 and 2019*

Graduate Assistantship from Department of Economics at IU

*2017-2020*

Midwest Econometrics Group Conference

*Oct, 2018 and 2019*

Jordan River Economics Conference

*Apr. 2018*

## TEACHING

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### Statistical Analysis for Business and Economics

*Fall 2018/19 and Spring 2019/20*

*Instructor, full teaching responsibilities*

- Lectured advanced statistical concepts, e.g. hypothesis testing, to undergraduate students; identified and resolved learning obstacles for students; evaluated student performance and provided tailored feedback.

Introduction to Microeconomics, teaching assistant

*Fall 2015, Spring 2016*

Introduction to Macroeconomics, teaching assistant

*Fall 2016, Fall 2017*

Survey of International Economics, teaching assistant

*Spring 2017*

Money and Banking, teaching assistant

*Spring 2017*

## SKILLS

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- Coding: MATLAB, Python, SQL, R, STATA, Fortran.
- Time Series and forecasting, statistical and econometric modeling, Statistical learning.

## REFERENCES

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