Unemployment in Production Networks

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1. Research Questions

In this paper, we are interested in answering the following questions:

- What is the impact of sector-specific productivity shocks on the aggregate labor market?
- How do production linkages amplify the impact of these shocks?
- How do sectoral unemployment rates respond to idiosyncratic shocks and comove based on input-output linkages?

2. Addressing Gabe's Comments

- Do the formulas for mismatch unemployment (e.g. Sahin et al., AER 2014) change if there is a network structure in production? And could you implement such generalized formulas? This would be a concrete project.
  - What Sahin et al is doing:
    * Data: introduce the use of the Conference Board's Help Wanted OnLine (HWOL) database. Allows them to define labor markets as a combination of location and industry.

Brown University.

    * Comparing social planner solution with market outcome, constructing a mismatch unemployment index. Optimality implies equal efficiency-weighted vacancy-unemployment ratios across sectors.
  - How we differ:
    * What is the optimality condition here? I suspect it will be some form of upstreamness-weighted tightness. (We should derive this)

- In this literature, it is important to derive structurally interpretable relationships. So start with theory. But you should be able to get to something with empirical content and implement it.

- The case of fully immobile labor across sectors is very stark. For example, it rules out spillovers across labor markets through job-seekers switching sectors. This seems important for the question you ask.

- I am not convinced ex ante that there will be a Leontief-inverse relationship in general. Certainly you can solve a Long-Plosser economy with fully immobile labor. And in that environment sectoral unemployment is isomorphic to a productivity shock. So is anything that shifts the ratio of non-production to production workers. But I think things become more complicated when there are cross-sector linkages in labor as well as in product markets, as happens when labor is not fully mobile. I can also see that this becomes much more complicated, so it merits some thought how to proceed.

- The issue of sectoral mobility also has implications for how you go to the data. We don't usually observe what sectors workers search in. The CPS or SIPP will report their previous sector of work, but most individuals who go through unemployment change sector (see. e.g. p.12 of https://scholar.harvard.edu/files/chodorow-reich/files/secular_labor_reallocation_appendix.pdf). There may be data sets in other countries that observe online job applications.

- To summarize, once you open the question to labor markets, restricting cross-market linkages to product markets feels restrictive. But it also complicates matters quite a bit otherwise. Think on this further and send me an update before we meet.

3. Related literature

- Jovanovic and Moffit (1990)

- Use the National Longitudinal Survey of Young Men (NLS)–a panel data set that that allows them to observe young men in their 20s and 30s in pairs of years from 1966 to 1980. Restrict the sample to people over 21, who have completed schooling and military service, leaving 9,963 observations. Observe real hourly wages, age, education, years of experience, and race. Are interested in whether someone has switched jobs and sectors between two survey periods.
- Model with no production linkages across firms. All firms hire essentially the same type of labor $\Rightarrow$ Wages per unit of productivity equalize across sectors in equilibrium.
- Model features workers who live for two periods. They are matched to a firm in the first period of their life, and draw firm-worker specific productivity m from a distribution with CDF $F(\cdot)$. Workers can choose whether to leave their firm at the end of the first period. If they choose to leave, are matched again and draw a new m based on the same distribution. If they choose to stay with their current firm, they keep their original m. $\Rightarrow$ leads to a threshold rule: all workers with first period draws above some level m^* stay with their firms, all others leave and get rematched. **Conclusions: Separation is endogenous. Wages and separation rates are procyclical. Separat rates are higher when the variance in firm productivity levels is higher.**
- Using NLS, find that movers have wage rates almost 8 percent below those of nonmovers. Evidence for other predictions of the model is less convincing.
- Find that matching consideration (whether a given worker is a good fit for a given job) are more important to labor mobility than sector specific shocks.
- Find that workers' ability to change jobs generates social value equivalent to about 6 to 9 percent of GDP.

• Lee and Wolpin (2006)

  - **Ask**: Does the staggering relative growth of employment in the US service sector from 57 percent to 75 percent from 1950 to 2000 despite essentially constant wages relative to goods workers imply that individuals dace small costs of switching between sectors? **Answer**: No, mobility costs are large. So large, in fact, that output in both services and manufacturing would have been double their level in 2000 if mobility costs could have been eliminated.
  - Also explore persistence of intersectoral wage differences.

- Data: Employment, wages, and school enrollment from the March supplements of the CPS from 1968 to 2001. Sectoral output and capital from BEA. Employment transitions from the NLSY79.
- Basic model features: Two sectors: services and goods producers. Firms with CES production function in three types of labor inputs and capital. Individuals choose between working in one of the six sector occupations, attending school, or remaining in the home sector. No production network linkages between sectors.
- Model of household occupation choice: Choice set featuring eight mutually exclusive alternatives: Working in one of the six industry occupations, education, or staying at home. At each time t workers decide which of the eight possibilities to pursue. Workers choose occupation to maximize utility, where utility for certain kinds of work can depend on education level, predisposition for certain kinds of work, etc.

- Sahin et al. (2014):

  (i) **Ask**: How much of the persistent rise in unemployment from 2006 to roughly 2014 can be explained by misallocation reducing matching efficiency? **Answer**: At most one third.

  (ii) Characterize solution to social planners problem where the social planner is able to flexibly and costlessly move unemployed workers across sectors. In the most general model, sectors differ in their matching efficiencies, productivity, and separation rates, and number of vacancies, which all follow an exogenous process (ultimately, they are all assumed to follow martingale sequences). Matches are generated by a Coubb-Douglas matching function in unemployment and vacancies with common unemployment intensity parameter. Mismatch is defined as $M = 1 - \frac{h}{h^*}$ the fraction of hires lost because of misallocation.

  (iii) **Vacancy data**: Vacancy data from JOLTS: provides survey based vacancy data starting in 2000 for 17 industries corresponding to two-digit NAICS. Vacancy data from HWOL Conference Board dataset: Covers roughly 16,000 online job boards and provides detailed information about the characteristics of advertised vacancies for 3 to 4 million unique active ads each month. HWOL database started in 2005.

  (iv) **Unemployment data**: Unemployment counts from CPS for industry level unemployment. Local Area Unemployment Statistics (LAUS from BLS) for geographic unemployment at county and MSA level.

(v) From these two sources, estimate a vacancy intensity of 0.5 for their matching function.

(vi) **Productivity data**: Compute industry level productivity by dividing BEA value added measures by average employment from the Establishment Survey. At occupation level, use annual data on average hourly wages from the Occupational employment survey. At county level, use median weekly earnings from Quarterly Census of Employment and Wages. Focus on relative wage movements over time, since wages may depend on more than just productivity.

(vii) **Job destruction data**: For industry level, use separation rates from the Business Employment Dynamics (BED) as the ratio of gross jobs to employment. Because job destruction rates by occupation are not available, compute the employment to unemployment transition rates by occupation in the last job from the CPS semi-panel. (Maybe we could use resume data to do this better.)

- Chodorow-Reich and Wieland (2019)
- Schubert, Stansbury, and Taska (2022)

4. Toy Model: Vertical Economy

4.1. Labor demand

For simplicity, we assume a vertical economy:

$$y_1 = A_1 N_1^{\alpha_1},\ y_2 = A_2 N_2^{\alpha_2} y_1^{\beta_2}.$$

The sector recruits production workers with recruiters R_i, who can each produce $\frac{1}{\kappa_i}$ vacancies V_i, and pay wage w_i to all employees $L_i^d = N_i + R_i$. Letting τ_i denote the recruiter-producer ration, $\frac{N_i}{R_i}$, sector 1 solves

$$\max_{N_1} A_1 N_1^{\alpha_1} - w_1(1+\tau_1)N_1.$$

The first order condition governing the sector's optimal employment choice is

$$\alpha_1 A_1 N_1^{\alpha_1 - 1} = w_1(1+\tau_1).$$

This implies that the demand for production workers is

$$N_1^d = \left(\frac{\alpha_1 A_1}{w_1(1+\tau_1)}\right)^{\frac{1}{1-\alpha_1}},$$

which implies that

$$L_1^d = (1+\tau_1)N_1^d = (1+\tau_1)\left(\frac{\alpha_1 A_1}{w_1(1+\tau_1)}\right)^{\frac{1}{1-\alpha_1}} = \left(\frac{\alpha_1 A_1}{w_1(1+\tau_1)^{\alpha_1}}\right)^{\frac{1}{1-\alpha_1}}$$

Similarly, for sector 2, we have that the following maximization problem:

$$\max_{N_2} A_2 N_2^{\alpha_2} A_1^{\beta_2} N_1^{\alpha_1\beta_2} - w_2(1+\tau_2)N_2 - y_1.$$

The first order condition governing the sector's optimal employment choice is

$$\alpha_2 A_2 N_2^{\alpha_2-1} A_1^{\beta_2} N_1^{\alpha_1\beta_2} = w_2(1+\tau_2).$$

This implies that the demand for production workers is

$$N_2^d = \left(\frac{\alpha_2 A_2 A_1^{\beta_2} N_1^{\alpha_1\beta_2}}{w_2(1+\tau_2)}\right)^{\frac{1}{1-\alpha_2}},$$

which implies that

$$L_2^d = (1+\tau_2)N_2^d = (1+\tau_2)\left(\frac{\alpha_2 A_2 A_1^{\beta_2} N_1^{\alpha_1\beta_2}}{w_2(1+\tau_2)}\right)^{\frac{1}{1-\alpha_2}} = \left(\frac{\alpha_2 A_2 A_1^{\beta_2} N_1^{\alpha_1\beta_2}}{w_2(1+\tau_2)^{\alpha_2}}\right)^{\frac{1}{1-\alpha_2}}.$$

Substituting in the value for N_1, we have that:

$$L_2^d = \left(\frac{\alpha_1 A_1^{\frac{1}{\alpha_1}}}{w_1(1+\tau_1)}\right)^{\frac{\alpha_1}{1-\alpha_1}\frac{\beta_2}{1-\alpha_2}} \left(\frac{\alpha_2 A_2}{w_2(1+\tau_2)^{\alpha_2}}\right)^{\frac{1}{1-\alpha_2}}.$$

To close the model we need to make an assumption about labor supply, which together with balanced flows with will pin down τ_1 and τ_2.

4.2. Labor supply and equilibrium with immobile labor

Suppose labor is fully immobile across the two sectors. Workers in sector i face exogenous separation rate s_i. Matches between unemployed workers and vacancies at firms are generated by a Cobb-Douglas matching function $m_i(U_i, V_i) = \omega_i U_i^{\eta_i} V_i^{1-\eta_i}$, where U_i and V_i are unemployment and vacancies. We assume that households supply their endowment of labor in-elastically: If they have a job they work the full amount that they can. Assuming balanced flows, the labor supply in sector i is determined by

$$\begin{aligned}
s_i L_i &= f(\theta_i) U_i \\
&= \omega_i \theta_i^{1-\eta_i} U_i \\
&= \omega_i \theta_i^{1-\eta_i} (H_i - L_i) \\
\Rightarrow L_i^s(\theta_i) &= \frac{\omega_i \theta_i^{1-\eta_i}}{s_i + \omega_i \theta_i^{1-\eta_i}} H_i
\end{aligned}$$

The equilibrium tightness, which we can use to fully characterize equilibrium employment and unemployment. Balanced flows also implies that the recruiter-producer ratio is a function of θ_i.

$$\begin{aligned}
s_i L_i &= q(\theta_i) V_i \\
\Leftrightarrow \kappa_i s_i (N_i + R_i) &= \omega_i \theta_i^{-\eta_i} R_i \\
\Leftrightarrow \kappa_i s_i (\tau_i^{-1} + 1) &= \omega_i \theta_i^{-\eta_i} \\
\Leftrightarrow \tau_i(\theta_i) &= \frac{\kappa_i s_i}{\omega_i \theta_i^{-\eta_i} - \kappa_i s_i}.
\end{aligned}$$

In equilibrium, labor supply equals labor demand in industry i

$$L_i^s(\theta_i) = L_i^d(\theta_i, \theta_j).$$

This equilibrium condition must hold in both industries, jointly pinning down θ_i in each industry.

4.3. Labor supply and equilibrium with fully mobile labor

Suppose, instead, that labor is fully mobile across the two sectors. Both firms hire from the same pool of workers, H; matches are governed by a shared Cobb-Douglas matching function $m(U, V)$. The total number of vacancies is $V = V_1 + V_2$. The relevant tightness that determines the vacancy filling rate of both firms depends on the total number of vacancies. But the number of positions each firm fills depends on the number of vacancies it posts as well as the aggregate tightness. Assuming balanced flows, the labor supply is now governed by a single common condition

$$L^s(\theta) = \frac{\theta^{1-\eta}}{s + \theta^{1-\eta}} H$$

Labor demand is still determined within each firm, but now depends the common aggregate vacancy filling rate. Assuming balanced flows within each firm,

$$sL_i = q(\theta)V_i$$

(Notice that balanced flows within each firm implies that flows are balanced for the labor market as a whole.) The recruiter-producer ratio satisfies

$$\kappa s(N_i + R_i) = q(\theta)R_i \Rightarrow \tau_i(\theta) = \tau(\theta) = \frac{\kappa s}{\omega\theta^{-\eta} - \kappa s}$$

[1] Now, market clearing requires that total labor demand across the two sectors equals the aggregate labor supply.

$$L^s(\theta) = L_1^d(\theta) + L_2^d(\theta)$$

This equation implicitly defines θ, and therefore allows us to fully characterize equilibrium employment and unemployment.

4.4. Labor supply and equilibrium in intermediate case

Finally, suppose that labor is only partially flexible across the two sectors. This is the most accurate characterization of the real world, where some workers within each industry are fairly substitutable across industries, while others workers with industry specific skills are not particularly substitutable. Assume, for instance, that a fraction λ_i of workers employed in industry i have general skills applicable to both industries, while a fraction $1 - \lambda_i$ have industry specific skills.

[1] NOTE FOR SELF: I WONDER IF ALLOWING KAPPA TO VARY ACROSS THE TWO FIRMS WOULD BE ISOMORPHIC TO ALLOWING PARTIAL FLEXIBILITY, AND PERHAPS AN EASIER WAY TO IMPLEMENT COMPUTATIONALLY.

The effective size of the labor force in industry i is then $H_i + \lambda_j U_j$, where j is the other industry. The total number of workers searching for jobs in industry i is $U_i + \lambda_j U_j$. Define $\theta_i = \frac{U_i + \lambda_j U_j}{V_i}$ as the sector i labor market tightness. The job finding rate in sector i is then

$$f_i(\theta_i) = \frac{m(U_i + \lambda_j U_j, V_i)}{U_i + \lambda_j U_j} = \omega_i \theta_i^{1-\eta}$$

Assuming balances flows, labor supply in sector i satisfies

$$\begin{aligned} s_i L_i &= f_i(\theta_i)(U_i + \lambda_j U_j) \\ &= f_i(\theta_i)(H_i - L_i + \lambda_j(H_j - L_j)) \\ \Rightarrow L_i^s(\theta_i, \theta_j) &= \frac{f_i(\theta_i)}{f_i(\theta_i) + s_i}(H_i + \lambda_j(H_j - L_j)) \end{aligned}$$

Similarly,

$$L_j^s(\theta_j, \theta_i) = \frac{f_j(\theta_j)}{f_j(\theta_j) + s_j}(H_j + \lambda_i(H_i - L_i))$$

Assuming balanced flows, the recruiter producer ratio in industry i is characterized by

$$\begin{aligned} s_i(N_i + R_i) &= q_i(\theta_i)V_i \\ \Rightarrow \tau_i(\theta_i) &= \frac{\kappa_i s_i}{q_i(\theta_i) - \kappa_i s_i} \end{aligned}$$

The equilibrium conditions are the following:

$$\begin{aligned} L_1^s(\theta_1^*, \theta_2^*) &= \frac{f_1(\theta_1)}{f_1(\theta_1) + s_1}(H_1 + \lambda_2(H_2 - L_2^d(\theta_2^*))) = L_1^d(\theta_1^*) \\ L_2^s(\theta_1^*, \theta_2^*) &= \frac{f_2(\theta_2)}{f_2(\theta_2) + s_2}(H_2 + \lambda_1(H_1 - L_1^d(\theta_1^*))) = L_2^d(\theta_2^*, \theta_1^*) \end{aligned}$$

5. Data

5.1. Job Postings

- Coverage: 2007 - 2021
- Available files linked by BGTJobId:
  - Main: the most information, as shown in table 1

- Certs: certification requirement, including things like driver's license and electrician certifications.
- Degree: degree requirements, such as professional degrees, bachleor's degree etc.
- Major: major requirements, such as accounting etc.
- Skills: skill requirements, such as economic analysis and Microsoft windows.

TABLE 1. Variables available in **main** from 2007 to 2020

Name	*Name*	*Name*	*Name*
BGTJobId	Specialty	City	Edu
JobId	BGTOcc	State	MaxEdu
JobDate	BGTOccName	County	Degree
CleanTitle	BGTOccGroupName	FIPSState	MaxDegree
CanonTitle	BGTOccGroupName2	FIPSCounty	Exp
OccFam	BGTCareerAreaName	FIPS	MaxExp
OccFamName	BGTCareerAreaName2	Lat	MinSalary
SOC	Employer	Lon	MaxSalary
SOCName	Sector	BestFitMSA	MinHrlySalary
ONET	SectorName	BestFitMSAName	MaxHrlySalary
ONETName	NAICS3	BestFitMSAType	PayFrequency
	NAICS4	MSA	SalaryType
	NAICS5	MSAName	JobHours
	NAICS6		TaxTerm
			Internship

MSA:Metropolitan Statisical Area. SOC: Standard Occupational Classification. ONET: Occupational Information Network. FIPS:Federal Information Processing Standards

5.2. Resume Date

5.3. Wages

Need to think about whether we need wages and if so why? Could we use wage data from the CPS to supplement the data from Burning Glass?

5.4. Production linkages

BLS input output tables.

TABLE 2. Variables in other files

Skill	*Certs*	*Degree*	*CIP*	*major*
BGTId	BGTJobId	BGTJobId	BGTJobId	BGTJobId
JobDate	JobDate	JobDate	JobDate	JobDate
Skill	Certification	DegreeLevel	CIP	STDMajor
SkillCluster	Salary	Salary	Salary	Salary
SkillClusterFamily				
IsSpecialized				
IsBaseline				
IsSoftware				
Salary				

Degree levels go from 01 to 22. Click here to see what they mean. CIP stands for the Classification of Instructional Programs.

TABLE 3. Variables available in resume data

cert_info	**edu_info**	**job_info**	**personal_info**	**skill_info**
BGTResID	BGTResId	BGTResId	BGTResId	bgtresid
CertificationName	DegreeLevel	JobId	StateName	SkillId
CertificationType	Institution	JobPosition	City	SkillName
CertificationPosition	SchoolCity	ONETCode	County	SkillClusterNa
	SchoolStateCode	CIPCode	ZipCode	SkillClusterFa
	DegreePosition	JobCleanTitle	NoofJobs	IsBaseline
	Degree	JobAddressState	NoofCertifications	IsSoftware
	Major	JobAddressCity	noofschooldegrees	IsSpecialized
	MajorCIPCode	CIPCode		
	CompletionDateRaw	NAICS2		
	GPA	NAICS4		
	GPAmax	CleanEmployer		
		NAICS2		
		NAICS4		
		JobDateRange		