Research Opportunities Using RDC-Accessible Data

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- 1. Overview of LEHD
- 2. Description of Current Research
- 3. Other Avenues for Future Research
- 4. Disclosure Avoidance Review

Overview of the LEHD

- Longitudinal Employer-Household Dynamics (LEHD) database:
 - Job-level sampling frame covering a near universe of worker-establishment matches from the U.S.
 - Based on quarterly UI records
 - Records contain worker IDs, firm IDs and quarterly job earnings
 - Merged with firm and estab. info. (e.g. geo. location, industry, firm age)
 - Merged with worker info. (age, race, gender, country of origin, some residential location)
 - First cluster of states enter in 1990, nearly all states present by 2004
 - Potential to merge with survey data (CPS, ACS, SIPP)

Project #1: Projecting the Incidence of Local Labor Demand Shocks

- Have U.S. local labor markets become more geographically integrated since the internet arrived?
- If so, for which types of workers and which types of industries?
- What are the implications of the structure of local labor market networks for the incidence of local labor demand shocks?
- How does the distribution of employment and wages across geographic areas and across worker skill types change when:
 - A Toyota plant moves from Ohio to Georgia?
 - A large Google office moves from California to Colorado?
 - A set of tech start-up subsidies is provided in Boise?
 - A hurricane wipes out all businesses located in a ten mile stretch along the Florida coast?
 - A stimulus project creates 300 construction jobs in Casper?

Project #1: Projecting the Incidence of Local Labor Demand Shocks

- Since observe all job-to-job transitions between *t* and *t* + 1, and can pinpoint estab. locations:
 - ⇒ Assign each worker-firm match at time *t* to types (rows) based on observable worker, firm, job characteristics.
 - Same for time *t* + 1 job matches (columns) ...
 - ⇒ Can populate a transition matrix capturing the transition from set of time t to time t + 1 job matches in quarter or year

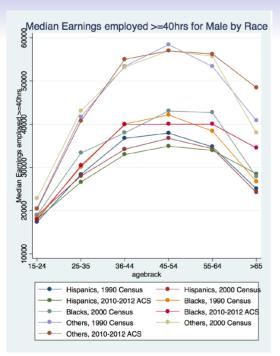
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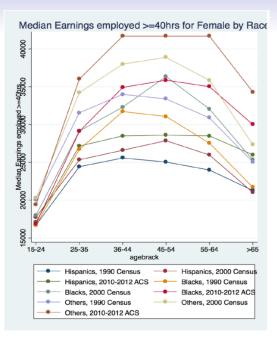
Project #1: Projecting the Incidence of Local Labor Demand Shocks

- Advances in the econometrics of estimating two-sided matching models ⇒
- Distill underlying propensity for certain transition types to take place above and beyond what could be predicted based on beginning- and end-of-year job composition.
- Use inferences about job-matching technology to construct simulations of how labor market will respond to labor demand shocks of the types suggested above.
- Akin to a big game of musical chairs!
- How does the composition of the labor demand shock (and the composition of the local labor supply) affect the incidence of the shock?

- Earnings Distributions by Race and Gender tend to diverge from labor market entry (\sim age 22) through mid career (\sim age 55)
- Exact patterns differ by race-gender combination and by cohort.
- How much of this divergence can be attributed to:
 - 1. Differential sorting to early career job types with different career paths (e.g. dead-end jobs!)?
 - Differential rates of promotion within-firms conditional on job type?
 - Differential rates of firm-to-firm job transitions conditional on job type?
- Appropriate policy response to close gaps depends critically on the source of the divergence.







- Same two-sided matching framework as first project.
- Again, construct transition matrix with rows and columns being job match types at year *t* and *t* + 1
- This time, origin job types (existing positions) defined by (age, race, gender, earnings category, firm size, occupation, education)
- Destination job types (positions to be filled) defined by (earnings category, firm size, occupation)
- From transition matrix, can distill relative propensity for each position type to hire or promote hispanic women with a college education relative to non-hispanic white men with a high school education.

- Given estimated willingness of destination job types to substitute across different worker types ...
- Can estimate how earnings gaps at each age would converge if:
 - 1. education distribution were equalized across race-gender combos for incoming cohort
 - initial sorting to job types were equalized across race-gender combos
 - propensity to promote workers within firms were equalized across r-g combos

4. propensity to hire workers of each type from other firms were equalized across r-g combos.

- From surveys (Dec. Census, CPS, ACS), can project distribution of race-gender for next 20 cohorts to enter labor market.
- Also can project the flow of retirees over next 20 years.
- And BLS projects changes in labor demand by occupation.
- ⇒ Use model to predict how earnings distributions of age-race-gender-educ. combos will evolve over next 20 years!
- Which groups will experience substantial earnings growth?
- Which should we be particularly worried about?
- How would the projections change if we made a major educational investment to keep young men from dropping out?
- How would projected earnings change if automation dramatically shrank the number of jobs in the transportation industry ... or the retail industry?

Other Potential Avenues of Research Featuring the LEHD

- Which jobs are dead-end jobs?
- What happens to firms when workers retire? What happens to the labor market for young and mid-career workers when many workers retire (or don't!)?
- Recent decreases in labor market and firm volatility: are the two related? If so, which causes which?
- Which occupations and industries are the most deleterious to long-run health?

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Disclosure Avoidance Review

- Design study to guarantee minimal risk that worker or firm confidentiality will be breached.
- ⇒ hard to analyze particular small geographic area, large firm competition.
- Have a plan for what you would like to eventually disclose at the outset of the project.
- Construct primary sample in SAS or STATA, since Census-provided DAR code is only in these languages.
- Minimize the number of samples you use, and the number of times you request disclosures.
- Don't hardcode any numbers into programs, since these must also pass through DAR.