Aggregate Recruiting Intensity
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Comments by Steven J. Davis
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Overview of the Paper, 1

A very well-crafted paper that incorporates a recruiting intensity margin, decreasing returns in production at the employer level, and collateral constraints into an equilibrium model with frictional hiring and rich employer-level dynamics.

- The recruiting technology maps neatly to evidence on the micro behavior of employment growth, vacancies and hiring. The authors use this mapping and evidence to discipline the choice of key parameter values.
- The analysis delivers a coherent interpretation of prominent patterns in the micro data, and it shows how aggregate shocks drive fluctuations in matching “efficiency” through their effects on average recruiting intensity. In turn, matching efficiency affects job-finding rates, job-filling rates and hiring.
Overview of the Paper, 2

The analysis quantifies three mechanisms whereby aggregate shocks drive (average) recruiting intensity:

• **Slackness effect:** Average recruiting intensity (RI) falls when job seekers per vacancy rise. The main quantitative force behind RI fluctuations, according to the authors.

• **Composition effect:** A negative aggregate shift causes a leftward shift in the distribution of employer growth rates, including a decline in entry and young-employer expansion, reducing average RI. A small force.

• **Sectoral mix effect:** Matching efficiency is very high in the Construction sector. So a cyclical shift away from Construction lowers the economy-wide average matching efficiency (equivalent to an RI drop, given Cobb-Douglas). An important force in certain episodes.
New Testable Implications

The GMV model also has rich implications for how recruiting intensity varies by employer age and how the cross-sectional distribution of vacancies, hiring and recruiting intensities respond to financial shocks and to common productivity shocks.

We currently have little evidence that speaks directly and powerfully to these implications. It’s a good topic for future empirical work that integrates JOLTS micro data with data on the production and financial characteristics of individual employers.
Standard Matching Function (SMF)

The standard aggregate matching function relates the flow of hires \( (H) \) to the number of job vacancies \( (V) \) and the number of job seekers \( (U) \), according to a CRS Cobb-Douglas function:

\[
H = \mu V^{1-\theta} U^\theta \implies \frac{H}{V} = \mu \left( \frac{U}{V} \right)^\theta
\]

where \( H/V \) is the vacancy yield, a raw version of the vacancy-filling or job-filling rate not corrected for time aggregation.
A Simple Check on the Empirical Performance of the Standard Aggregate Matching Function

Elasticity parameter, $\theta$, set to 1/2 in calculating implied yields.

Reproduced from Figure 1 in Davis, Faberman and Haltiwanger (2013).
Sources of Instability in the SMF – AKA Fluctuations in Matching Efficiency

1. Mismeasurement of job seekers
2. Mismeasurement of effective vacancies
3. Mismatch: Aggregating over markets that vary in tightness
4. Composition: Aggregating over markets that vary in matching efficiency
5. Changes in search technology, screening & evaluation technology, etc.

All of 1-5 are potential sources of instability in the SMF (fluctuations in $\mu$).
Improving on the SMF, 1

1. Measuring job seekers

2. Measuring effective vacancies

3. Mismatch: Aggregating over local markets that vary in tightness
   - Examples include Layard et al. (1991), Herz and van Rens (2011), Daly et al. (2012), Sahin et al. (2012), Estevao and Smith (2013).
Improving on the SMF, 2

4. Composition: Aggregating over markets that vary in matching efficiency
   – DFH (2012) and GMV (2016)

5. Search and sorting technologies, screening & evaluation technologies, etc.
   – Examples include Kuhn and Stuterud (2001), Stevenson (2009), and Kroft and Pope (2011)

Note: Stock-flow matching models imply that the SMF involves a rather profound mismeasurement of $U$ and $V$ inputs and a functional form misspecification. Examples of stock-flow matching models include Coles and Smith (1998), Petrongalo and Pissarides (2001, Section 3.5), and Shimer and Ebrahimy (2010).
## Construction Contribution to Changes in Job-Filling Rates During and After the Great Recession

Numbers in blue reflect a simple shift-share calculation

<table>
<thead>
<tr>
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<tbody>
<tr>
<td>Percent Change in National Job-</td>
<td>39.0</td>
<td>-22.0</td>
</tr>
<tr>
<td>Filling Rate Relative to 2007Q4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Construction Employment Share</td>
<td>4.7</td>
<td></td>
</tr>
<tr>
<td>As of 2007:4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percent of National Change</td>
<td>43.0</td>
<td>41.9</td>
</tr>
<tr>
<td>Accounted for by Construction</td>
<td></td>
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</tbody>
</table>

Reproduced from Table 1 in Davis, Faberman and Haltiwanger (2012, AER P&P). Authors’ calculations using JOLTS data.
Restating a Key Finding in DFH, 1

**GMV:** “The robust finding of DFH is that firms that grow raster fill their vacancies at a faster rate.”

**My restatement:** Looking across sectors and employers, and looking over time for a given employer, the vacancy-filling rate rises with the gross hires rate.

The two statements are equivalent only in a world with no replacement hiring.
I prefer my restatement for several reasons:

- Replacement hiring is huge: worker flows are at least twice as large as job flows.
- Worker and job flows exhibit distinct patterns of variation in the C-S and over time.
- The matching function aggregates gross hires over employers, not gross job creation.
- Accordingly, the key elasticity that DFH estimate from JOLTS micro data – and to which GMV calibrate their recruiting technology – derives from the empirical relationship between vacancy-filling rates and gross hires rates.
Replacement Hiring

GMV consider an extended model with on-the-job search, quits and replacement hiring. The extension posits an exogenous quit rate that is invariant in the C-S and over time. Empirically, the quit rate varies systematically in the C-S of employer growth rates. Moreover, the quit rate is highly sensitive to the cycle *conditional* on an employer’s growth rate, and this sensitivity varies a lot with the employer growth rate. The next slide illustrates these facts. See DFH (2012a) for more.
Quarterly Quit Rates in the C-S & Over Time

Reproduced from Figure 8.d in Davis, Faberman and Haltiwanger (2012a)
Does GMV Analysis Understate Role of the “Composition” Effect?

1. Relative to their employment, young employers make up a disproportionate share of gross job creation. They are also cyclically sensitive. The authors account for these facts in quantifying their composition effect.

2. But the young-employer share of gross hires is even greater than their share of gross job creation.
   - Why? Because all workers at young employers have short job tenures, and separation rates fall with tenure. Thus, young employers have higher rates of replacement hiring.
   - Thus, their composition analysis understates the cyclical shift in the young-employer share of gross hires.

So, yes, I think they underestimate the “composition” effect. Is this a big deal quantitatively? Probably not. But there are other composition effects as well.
Two RI Indices Compared, 1

Davis, Faberman and Haltiwanger (2013)

Strengths
• Captures all shifts in distribution of vacancies and hires across (a) employers that differ in recruiting intensities and (b) sectors that differ in matching efficiencies
• Readily disaggregates into market segments defined in observable employer characteristics (industry, size, turnover rates, etc.)
• Circumvents need to measure the effective number (and search intensities) of jobseekers

Weaknesses
• Neglects the slackness effect
Two RI Indices Compared, 2

Gavazza, Mongey and Violante (2016)

Strengths

• Incorporates the slackness effect
• Augmented version captures some changes in sectoral mix

Weaknesses

• Tied to a particular measure of jobseekers (the number of unemployed in GMV), a nettlesome matter
• Neglects distinction between gross job creation and gross hires
• Only captures explicitly modelled shifts across (a) employers that differ in recruiting intensities and (b) sectors that differ in matching efficiencies
Two RI Indices Compared, 3

• In short, the DFH and GMV recruiting intensity measures have very different sets of strengths and weaknesses.
• Both measures advance our understanding of the hiring process, matching efficiency, job-filling rates, etc. Both have material limitations.
• Downstream users may want to try both measures, recognizing that one of them may be more suitable for certain applications.
  – When capturing the slackness effect is essential, the GMV measure is clearly more suitable.
  – When it’s desirable to disaggregate by employer characteristics or capture a broad range of composition effects, the DFH measure is better.
Help Wanted: We Need Direct Measures of Recruiting Intensity

1. Both DFH and GMV develop clever(!) methods for extracting information about recruiting intensity from data sources that contain no direct measures of RI.

2. We need direct measures of recruiting intensity. An expanded JOLTS questionnaire is a natural vehicle for obtaining direct evidence on recruiting intensity (and many other poorly understood aspects of hiring behavior).

3. See Davis (2014) for a collection of concrete suggestions for improving the JOLTS, including a suggested question on recruiting intensity.
References, 1


References, 2


• Estevao, Marcello and Christopher Smith, 2013, “Skill Mismatches and Unemployment in the United States,” International Monetary Fund.


References, 3


• Stevenson, Betsey, 2009, “The Internet and Job Search,” in *Studies labor Market Intermediation*, University of Chicago Press.
