Hours and Wages

Alexander Bick  Adam Blandin  Richard Rogerson

August 2019
Introduction

Changing nature of what we mean by “micro-foundations”.

Today: Labor supply in the cross-section, with emphasis on intensive margin.

Our focus: Cross-sectional relationship between hours and wages.

Literature has mostly focused on first and second moments.

Message: First and second moments not enough.

Going beyond first and second moments has first order implications for labor supply responses, estimation of key preference parameters.
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Data

Key data: usual weekly hours and hourly wages on main job.


Sample Selection Criterion

Ages 25-64
Not enrolled in school, not self-employed
Weekly hours > 10, Implied wage > .5 federal minimum wage

Over 850,000 observations

Key patterns confirmed in other data sets: Census, ACS, NLSY79.
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Facts I: Distribution of Usual Weekly Hours (Males)

Key points:
- Heavy concentration in 40-44
- Little mass below 40
- Significant mass above 50 (almost 30% of total hours come from those with usual hours of 50 or more)
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We examine how hourly wages vary with hours in the cross-section. We run the following non-parametric regression using 5 hour bins:

$$w_i = \sum h H_i \beta_h + \gamma X_i + \epsilon_i$$

Note: regression is just data-description.
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Estimated Wage-Hours Profile

Key points:
- Non-monotonic
- Very similar for males and females
- Holds also by age, education and for many occupations.
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Is the Decreasing Portion an Artifact of Data Issues?

Three Potential Issues

1. Top-coding
2. Salaried workers with variable hours
3. Measurement error
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Facts III: Other Profiles
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(b) SD - All

The graph shows the standard deviation of hourly wages across different bins of usual weekly hours. The horizontal axis represents the hours bins (usual weekly hours), while the vertical axis shows the S.D. log of hourly wages. The data indicates that the standard deviation tends to stabilize after a certain number of hours.
Figure 10: Mean and SD of Hours by Wage Decile: Men

(a) Mean - All

(b) SD - All
A Simple Benchmark Model

Unit mass of individuals, with preferences:

\[ \log h_i = A \log z_i + B \log \alpha_i \]

where

\[ A = \frac{\sigma_1 \sigma_i}{\sigma_i + \gamma_i} \]

\[ B = \frac{1}{\sigma_i + \gamma_i} \]

Budget equation:

\[ c_i = w_i h_i \]
A Simple Benchmark Model

Unit mass of individuals, with preferences:

\[c_i = \frac{1}{\sigma} \alpha_i + \frac{1}{\gamma} h_i + \frac{1}{\gamma} \]

Budget equation:

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Optimal labor supply:

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where

\[A = \frac{\sigma_1}{\sigma + \gamma}\]

\[B = \frac{1}{\sigma + \gamma}\]
Unit mass of individuals, with preferences:

\[
\frac{1}{1 - (1/\sigma)} c_i^{1-\frac{1}{\sigma}} - \frac{\alpha_i}{1 + (1/\gamma)} h_i^{1+\frac{1}{\gamma}}
\]
A Simple Benchmark Model

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\]

where

\[
A = \left( \frac{\sigma - 1}{\sigma} \right) \left/ \left( \frac{1}{\sigma} + \frac{1}{\gamma} \right) \right.
\]

\[
B = -1 \left/ \left( \frac{1}{\sigma} + \frac{1}{\gamma} \right) \right.
\]
Calibration

Fix $\gamma$ and $\sigma$. In what follows $\sigma \neq 1$ and $\gamma = 0.50$.

Assume $(z_i, \alpha_i)$ are jointly log normally distributed.

No measurement error for now.

Six parameters: $\mu_z, \mu_\alpha, \sigma_z, \sigma_\alpha, \rho_{z\alpha}, w$, (but $w$ and $\mu_z$ not separately identified).

We choose these to match features of the cross-section.
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Table 1

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \mu_h )</td>
<td>3.74 ( \mu )</td>
</tr>
<tr>
<td>( \alpha )</td>
<td>11.2347</td>
</tr>
<tr>
<td>( \mu_w )</td>
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</tr>
<tr>
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</tr>
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</tr>
<tr>
<td>( \rho_{z,\alpha} )</td>
<td>0.067</td>
</tr>
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</table>

Note: If we consider an alternative value of \( \sigma \), then \( \rho_{z,\alpha} \) adjusts accordingly to "undo" the correlation between \( h \) and \( w \) induced by \( \sigma \).
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Calibration of Simple Model

<table>
<thead>
<tr>
<th>Data Moment</th>
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<tr>
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<td>$\mu_z = 0$</td>
</tr>
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<td>$std(\log h) = 0.122$</td>
<td>$\sigma_\alpha = 0.3415$</td>
</tr>
<tr>
<td>$std(\log w) = 0.460$</td>
<td>$\sigma_z = 0.4616$</td>
</tr>
<tr>
<td>$corr(\log w, \log h) = 0.067$</td>
<td>$\rho_{z\alpha} = -0.08$</td>
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Note: If we consider an alternative value of $\sigma_z$, then $\rho_{z\alpha}$ adjusts accordingly to "undo" the correlation between $h$ and $w$ induced by $\sigma_z$. 
Calibration to First and Second Moments

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A Good Model of the Micro Data? The Hours Distribution

(a) Distribution Over Hours Worked

![Graph showing distribution over hours worked with bars for data and model.](image)
A Good Model of the Micro Data? The Wage-Hours Profile
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An Extension of the Benchmark Model

We allow for a non-linear earnings function:

\[ c_i = z A(h(\theta )) = z E(h(\theta )) \]

Special case (French (2005), and many others since):

\[ E(h) = \bar{A} h \theta \]

Define the wage function as:

\[ W(h) = E(h) h = A(h) \theta(h) \]

Why might this help?

Interpretation: \( E(h) \) reflects the set of market opportunities available to a worker.
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\[ W(h) = \frac{E(h)}{h} = A(h)h^{\theta(h)-1} \]
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We generalize the previous calibration exercise so as to target not only the first and second moments but also:

- the hours distribution by ten hour bins
- the wage-hours profile by 5 hour bins.

We also add measurement error, classical measurement error in hours ($\sigma_m$), except for those who work 40 hours and wages.
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- except for those who work 40
We assume $(z_i, \alpha_i)$ are jointly log normally distributed as before.

Earnings function
We fix $\sigma$ and $\gamma$ as before, and fix measurement error.
Calibration Details

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- here we report on a step function specification with three regions (steps at 40 and 50)
We fix \( \sigma \) and \( \gamma \) as before, and fix measurement error.

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  - have tried several specifications
  - here we report on a step function specification with three regions (steps at 40 and 50)
  - parameters are \( \theta_s \), \( \theta_n \), and \( \theta_l \)
For today, we show estimates using data for males aged 50-54 with either high school or some college.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu$</td>
<td>12.869</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>1.199</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>0.501</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0.40</td>
</tr>
<tr>
<td>$z$</td>
<td>1.399</td>
</tr>
<tr>
<td>$\rho$</td>
<td>0.110</td>
</tr>
<tr>
<td>$\theta$</td>
<td>0.095</td>
</tr>
</tbody>
</table>
Estimates

For today, we show estimates using data for males aged 50-54 with either high school or some college.
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Table 2
Estimated Parameter Values

<table>
<thead>
<tr>
<th>$\mu_\alpha$</th>
<th>$\sigma_\alpha$</th>
<th>$\sigma_z$</th>
<th>$\rho_{\alpha,z}$</th>
<th>$\theta_s$</th>
<th>$\theta_n$</th>
<th>$\theta_l$</th>
</tr>
</thead>
<tbody>
<tr>
<td>-12.869</td>
<td>1.199</td>
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<td>-0.40</td>
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<td>0.110</td>
<td>0.095</td>
</tr>
</tbody>
</table>
## Model Fit: First and Second Moments

<table>
<thead>
<tr>
<th>Data Model</th>
<th>$\log h$</th>
<th>$\log w$</th>
</tr>
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<tbody>
<tr>
<td>Mean</td>
<td>3.244</td>
<td>2.804</td>
</tr>
<tr>
<td>Std</td>
<td>0.122</td>
<td>0.460</td>
</tr>
<tr>
<td>Corr</td>
<td>0.067</td>
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Hours and Wages August 2019 20 / 25
## Model Fit: First and Second Moments

### Table 3

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th>Model</th>
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<tbody>
<tr>
<td>mean (log $h$)</td>
<td>3.744</td>
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</table>
Model Fit: Hours Distribution
Model Fit: Hours Distribution
Model Fit: Wage-Hours Profile

Figure 14: Fit of Wages
Selection vs. Wage Function (vs. Measurement Error)

Figure 15: Model Wages: The Wage-Hours Menu vs. Selection

Figure 16: Model Wages: The Wage-Hours menu vs. Measurement Error
Implications

Consider embedding our (static) wage function into otherwise standard dynamic settings: Aiyagari-Bewley-Huggett heterogeneous agent incomplete markets model.

Life cycle labor supply setting

Key point: our specification implies a large kink in the earnings function at 40 hours, and that a lot (but not all) individuals are at the kink. This has important implications for labor supply responses in both settings.
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This has important implications for labor supply responses in both settings.
Our analysis suggests that there are important non-linearities in the budget sets faced by individual workers at a given point in time. These non-linearities have first order implications for labor supply responses.

Key next step is to extend the analysis to a dynamic setting in which current hours may influence future wages via learning by doing. Our analysis suggests that one cannot isolate the dynamic effects of hours on wages without incorporating static effects. Existing literature on dynamic effects has neglected this issue.
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Existing literature on dynamic effects has neglected this issue.