Hours and Wages

Alexander Bick Adam Blandin Richard Rogerson

August 2019

Introduction

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

Data

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Over 850,000 observations

Key patterns confirmed in other data sets: Census, ACS, NLSY79.

Facts I: Distribution of Usual Weekly Hours (Males)

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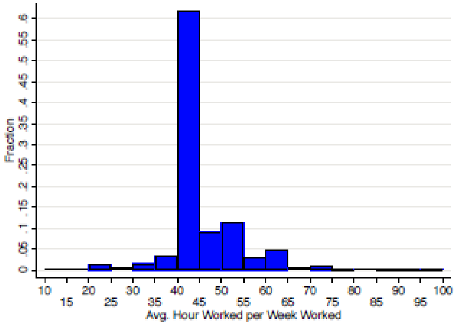

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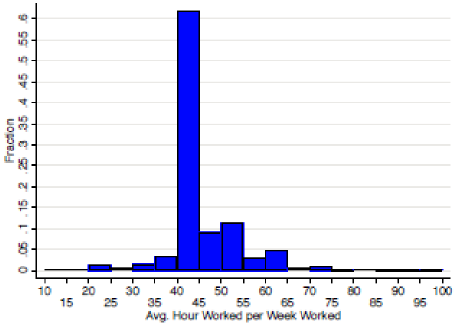

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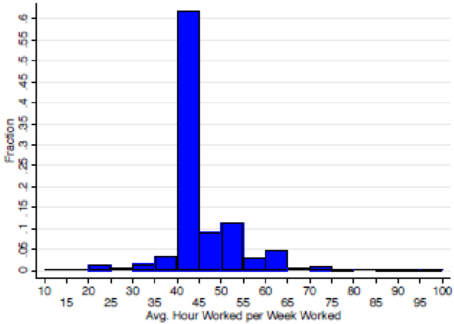

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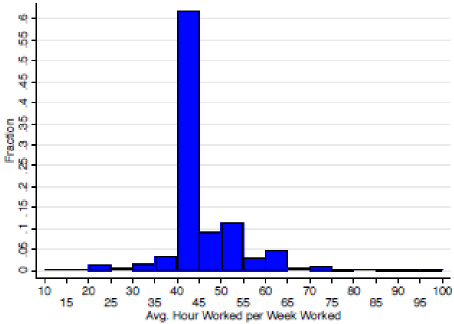

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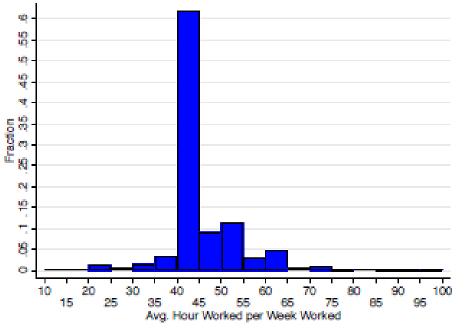

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- heavy concentration in 40-44
- little mass below 40
- significant mass above 50 (almost 30% of total hours come from those with usual hours of 50 or more)

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Note: regression is just data-description.

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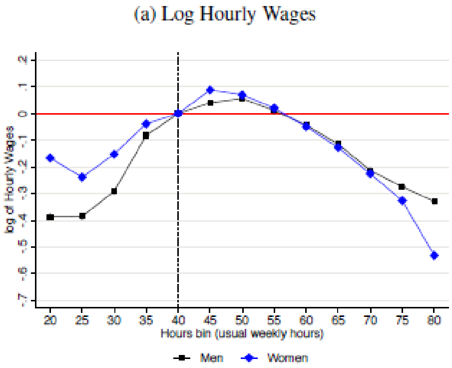

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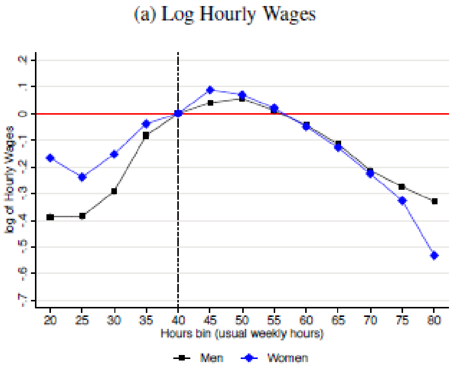

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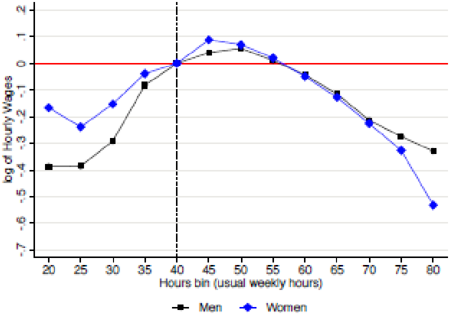

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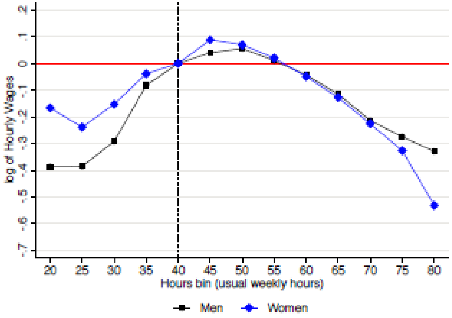

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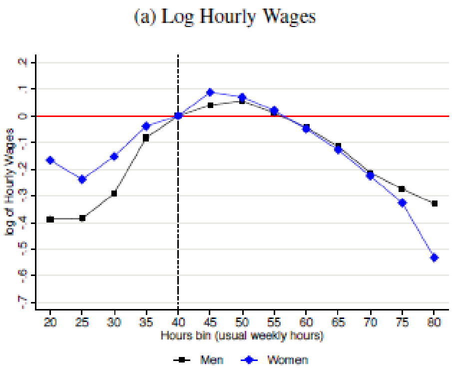
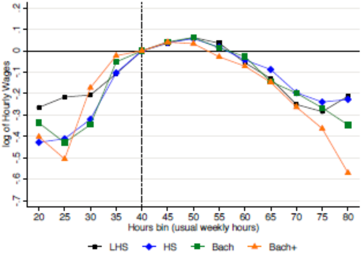


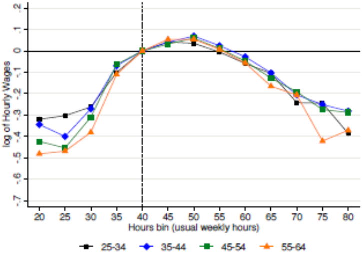
Key points:

- Non-monotonic
- Very similar for males and females
- Holds also by age, education and for many occupations.

(b) By Education



(a) By Age



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(b) SD - All

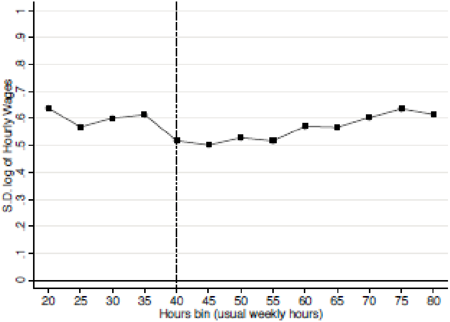
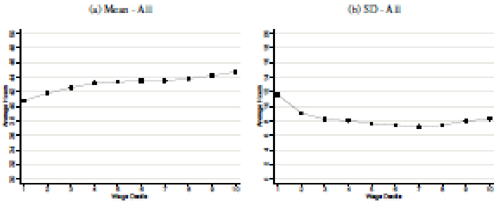


Figure 10: Mean and SD of Hours by Wage Decile: Men



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Optimal labor supply:

$$\log h_i = A \log z_i + B \log \alpha_i$$

where

$$\begin{aligned} A &= \left(\frac{\sigma-1}{\sigma}\right) / \left(\frac{1}{\sigma} + \frac{1}{\gamma}\right) \\ B &= -1/\left(\frac{1}{\sigma} + \frac{1}{\gamma}\right) \end{aligned}$$

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Six parameters: μ_z, μ_α, σ_z, σ_α, $\rho_{z\alpha}$, w,(but w and μ_z not separately identified).

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

Calibration to First and Second Moments

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Table 1
Calibration of Simple Model

Data Moment	Model Parameter
$mean(\log h) = 3.74$	$\mu_\alpha = -11.2347$
$mean(\log w) = 2.804$	$\mu_z = 0$
$std(\log h) = 0.122$	$\sigma_\alpha = 0.3415$
$std(\log w) = 0.460$	$\sigma_z = 0.4616$
$corr(\log w, \log h) = 0.067$	$\rho_{z\alpha} = -0.08$

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Note: If we consider an alternative value of σ then $\rho_{z\alpha}$ adjusts accordingly to "undo" the correlation b/w h and w induced by σ.

A Good Model of the Micro Data? The Hours Distribution

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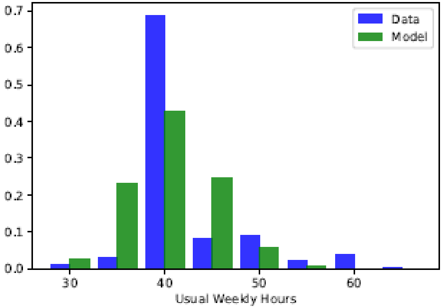
(a) Distribution Over Hours Worked



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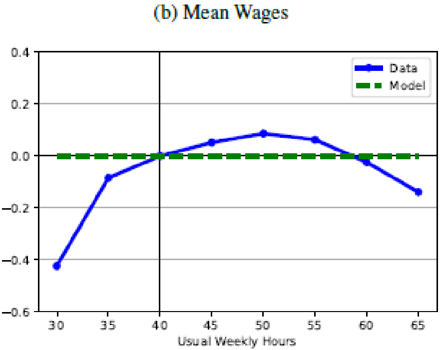

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Interpretation: $E(h)$ reflects the set of *market* opportunities available to a worker.

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- classical measurement error in hours (σ_m)
- except for those who work 40

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  - parameters are θ_s, θ_n, and θ_l

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Table 2
Estimated Parameter Values

μ_α	σ_α	σ_z	$\rho_{\alpha,z}$	θ_s	θ_n	θ_l
-12.869	1.199	0.501	-0.40	1.399	0.110	0.095

Model Fit: First and Second Moments

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Table 3

Fit of Estimated Model

	Data	Model
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Model Fit: Hours Distribution

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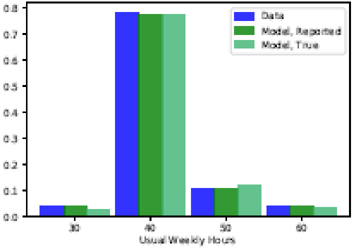
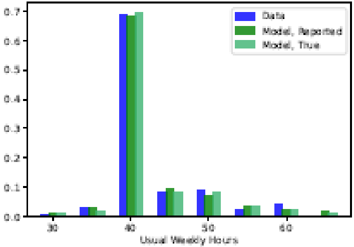
(a) 10-Hour Bins (Targeted)



(b) 5-Hour Bins



Model Fit: Wage-Hours Profile

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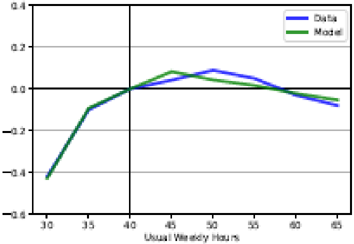
Figure 14: Fit of Wages



Selection vs. Wage Function (vs. Measurement Error)

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

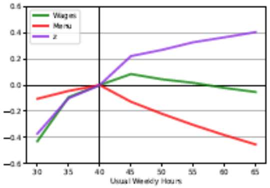
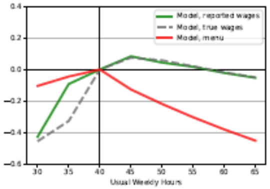


Figure 16: Model Wages: The Wage-Hours menu vs. Measurement Error



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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.

Summary/Future Work

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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.