Accounting for Job-to-Job Transitions: Wages Versus Values

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Motivation

- Job-to-job transitions are an important part of labor reallocation
    - 60% of new hires come directly from other jobs
    - 10% of workers each year make an EE transition
- Moving jobs is a common way of obtaining earnings increases
- Yet there appears to be a substantial amount of wage cuts
- Wage cuts are not necessarily puzzling from a dynamic perspective if they are associated with increases in *value*
- Key question: are these wage cuts associated with positive or negative changes in *value*?
- Important for understanding efficiency of the labor market, risk over the life cycle, policy design
    - Motivations for switching jobs affect the allocation of workers to firms and determine which features should be included in models
    - Link between labor market fluidity and welfare

Motivations for Wage and Value Changes

	- Wage	+ Wage
+ Value	Accept wage cut now in exchange for future wage growth: Postel-Vinay and Robin (2002)	Good move for both immediate wages and future wages
- Value	Non-wage amenities, forced moves: Sorkin (2018), Hall and Mueller (2018), Moscarini and Postel-Vinay (2019)	Borrowing constraints: Lise (2012), Luo and Mongey (2019)

What We Do

1. Refine measurement of job-to-job transitions
    - Made possible by high frequency administrative data from Denmark
    - Precise pinpointing of transition and clear wage measures
2. Compute wage change CDFs for stayers and switchers
3. Semi-parametric estimation of value of a job for a worker
    - Nest value functions in commonly used search models
4. Analyze the joint distribution of wage changes and value changes for job-to-job transitions
    - With model, we assign a change in value associated with every wage change we observe
    - Quantify value cuts, toward an understanding of who is taking them and why

Preview of Results

Measurement

- About half of job-to-job transitions feature a wage cut, but only a quarter of these are more than 10%
- But it makes a difference how you measure these!

Wages vs. values

- Changes in *value* are typically smaller in magnitude than wage changes
- 60% of wage cuts also feature declines in value
- Motivations for EE switches tend to be related to *unobservable* match + job characteristics
- Lots of variation as to whether future wages or future transitions are quantitatively responsible for the value changes

Related literature

Outline

Measurement and Motivating Facts

Model of Job Values

Results

Measurement and Motivating Facts

Data

Danish administrative registry data

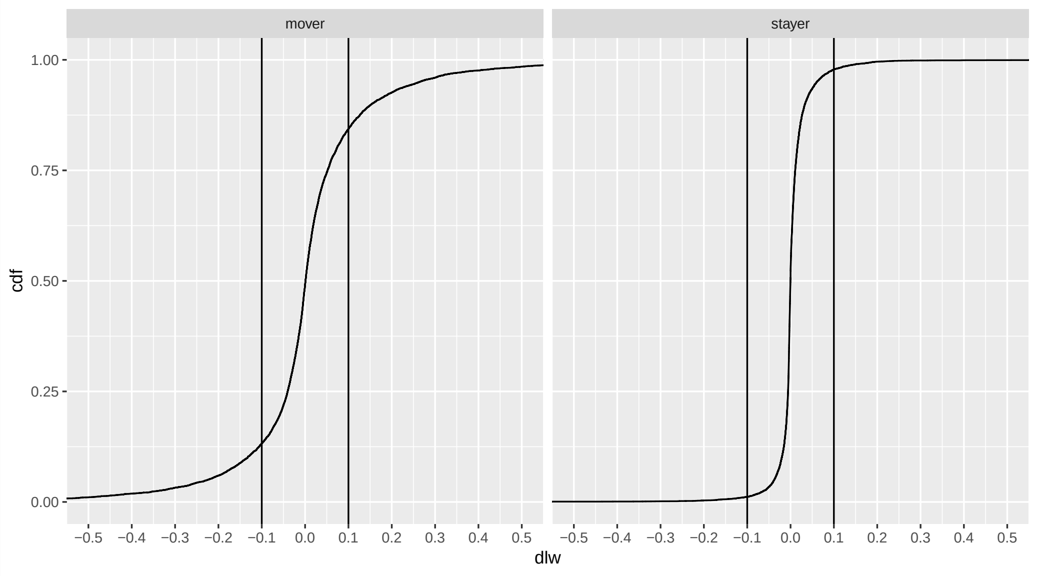
- Entire Danish population from 2008 to 2017
- Monthly payroll records reported by employers
- Total pay each month, firm ID, contractual hours, occupation, industry, demographics,. . .
- Public transfers database for unemployment and OLF states

What is a job?

- Firm $\times$ 2-digit occupation
- Why? Wages in same firm differ across occupation, relevant for model
- Cells under 1000 person-quarter observations are grouped by 4-digit industry $\times$ 2-digit occupation

Quarterly aggregation to keep model tractable, but still can track moves through U

Distribution of Wage Growth



How to Measure Wages

Construct measure of base real wage

- Issue: spikes during the last month, representing payouts from holiday fund
- Drop last wage observation + calculate 12-month centered moving average

Sample: full-time workers who are attached to the labor force

- Only consider jobs with contractual hours within 2% of 160 hours per month (full-time)
- Ensures measured wage change during job switch not driven by hours

Wage Growth for Switchers: Alternate Measurements

	Decrease > 10%	Increase > 10%
Baseline	0.13	0.14
Fail to drop last wage obs.	0.19	0.14
Looser hours restriction	0.17	0.18
Previous two combined	0.26	0.16

- Our adjustments reduce the noise present in the original data
- Careful measurement matters, especially at the tails

Model of Job Values

Objectives

- Want to translate our wage changes into *value* changes
- PDV of future wages in a job consists of:
  1. Wage stream in that job
  2. Transition rates to other jobs
- Need a model for
  1. Predicting wages for any worker in any job
  2. Predicting transitions between jobs for any worker
- Approach
  1. Define worker and job types
  2. Define state variables
  3. Estimate wage and transition as function of state variables by type
- How to pick state variables? Guided by theory. Today: a variant of the wage posting model of Burdett and Mortensen (1998)

Environment

Workers

- Workers can be one of $i \in I$ types (will drop i subscripts)
- Type-specific component of earnings: g
- Live from $a = 1, 2, \ldots, A$
- Age profile of earnings differs across types: $h(a)$

Jobs

- Workers transition between J jobs
- This set also includes non-employment states
- Piece-rate in each job: $\omega(j)$

Wages: $\omega(j)h(a)gz$

- z: match-specific productivity

Matches

- When matched to a job, workers have a match-specific productivity z
    - Helps match the wage changes of job switchers
- After moving $j \to k$, draw new z' from a distribution that depends on (j, k, z)
    - z' revealed if the match is created
    - Allow for persistence in z when workers switch between jobs
    - Productivity in new job may depend on the identity of the old job
- Stayers' wages are subject to i.i.d. mean 0 shocks ε
    - Helps match stayers' wage growth
- Contact rate from job j to k: $\lambda_k(a, j, z)$
    - Workers may be more likely to leave lower-paying jobs or jobs at which they're not productive

Value Function

$$v(a,j,z) = \overbrace{\omega(j)\,h(a)gz}^{\text{today's wages}}$$

$$+\beta\left[\sum_k \underbrace{\lambda_k(a,j,z)\,\mathbb{I}_{\{d(a,j,k,z)=1\}}\mathbb{E}_{z\times\varepsilon} v(a+1,k,z'\varepsilon')}_{\text{expected value of switching from job } j \text{ to job } k} + \underbrace{\Lambda(a,j,z)\,\mathbb{E}_\varepsilon v(a+1,j,z\varepsilon')}_{\text{expected value of staying at job } j}\right]$$

- Burdett-Mortensen: constant job-specific wage piece rate, probability of moving to other jobs depends on current job, no renegotiation in response to outside offers
- Generalizations: life-cycle, match-specific productivity, i.i.d. shocks to stayers' wages
- Instead of computing equilibria of structural model, calculate ingredients needed to solve for $v(a,j,z)$

Ingredients: $\omega(j)$, $h(a)$, $g, z, \lambda_k(a, j, z)$, expectations over z' for switchers

Worker types

- Correspond to 4 fixed education $\times$ gender categories

Job types j

- 6019 employment states (about half correspond to firm $\times$ occupation; other half corresponds to industry $\times$ occupation)
- 10 non-employment states: short- and long-term unemployment, retirement, maternity leave, sick leave, etc. that we observe transfers for

Age profile $h(a)$

- $w(j), z$ constant within match $\rightarrow$ average wage change between a and $a+1$ for stayers
- Pool across jobs and over time, take cumulative sum of earnings changes

WAGE PREMIA $\omega(j)$

Separate each component of earnings: $w_n(a,j,z) = \omega(j)h(a)gz$

- Selection issue: what if workers' mobility decisions are based on z?
- Averaging earnings within jobs and worker types would give biased estimates of $\omega(j)$
- Assumption: while unemployed, z is low enough such that all workers accept any job offer $\implies$ their distribution of z is the same across jobs

With g in hand, for jobs with enough hires from U, $\omega(j)$ is: How to estimate $g(i)$

$$\frac{1}{U_j}\sum_{n=1}^{U_j}\frac{w_n(a_n,j_n,z_n)}{h(a_n)g_n} = \frac{1}{U_j}\sum_{n=1}^{U_j}\frac{\omega(j)h(a)g\mathbb{E}[z]}{h(a)g} = \omega(j) \qquad \forall n : j_n = j$$

- Key: expectation over z is the same as the unconditional, normalized to 1 for all j
- For jobs less workers hired from U, impute $\omega(j)$ via statistical methods Details Scatter plot

Match-specific productivity

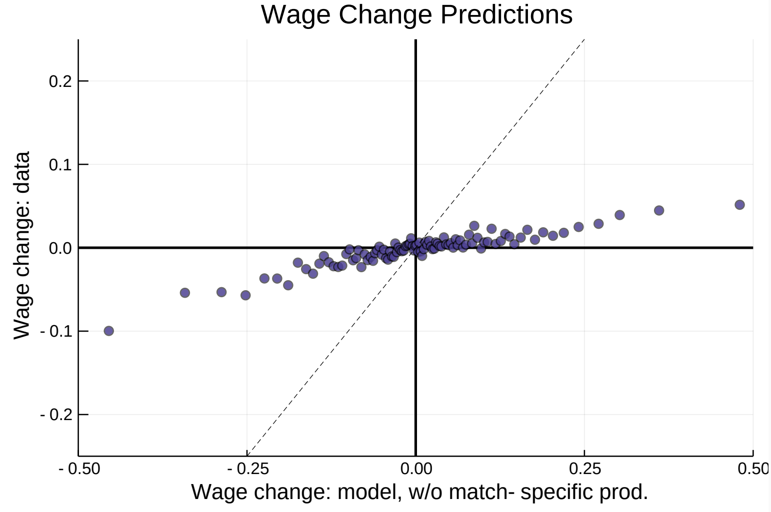
- Match-specific productivity z_n in data:

$$z_n = \frac{w_n(a_n, j_n, z_n)}{\omega(j_n)h(a_n)g_n}$$

- Necessary step for computing values: law of motion for z'
- Want to generate accurate wage predictions *at the individual level* so we can trust value predictions!
    - Model with and without z fit the overall CDF of wage changes well
- For job switchers from j to k, want to forecast z' as a function of the model's state variables: $z' = f(a, j, k, z)$
- Specification that yields the best forecast is:

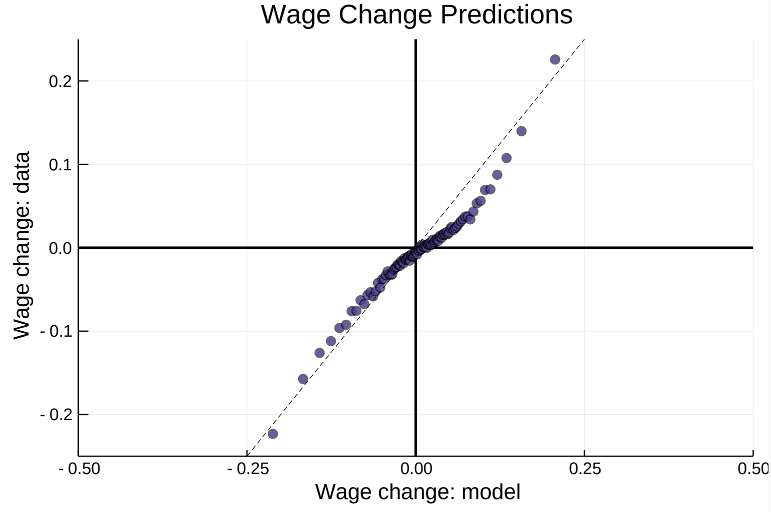
$$\log z_i' = \bar{z} + \rho \log z_i + \beta_1 \log \omega_i + \beta_2 \log \omega_i' + \beta_3 \text{mean}(z|\omega_i) + \beta_4 \text{mean}(z|\omega_i') + \beta_5 \text{var}(z|\omega_i) + \beta_6 \text{var}(z|\omega_i') + \eta_i$$

EE Wage Change Predictions: Without Match-Specific Productivity



- On their own, piece rates do not do well at predicting individual wage changes

EE Wage Change Predictions: With Match-Specific Productivity z

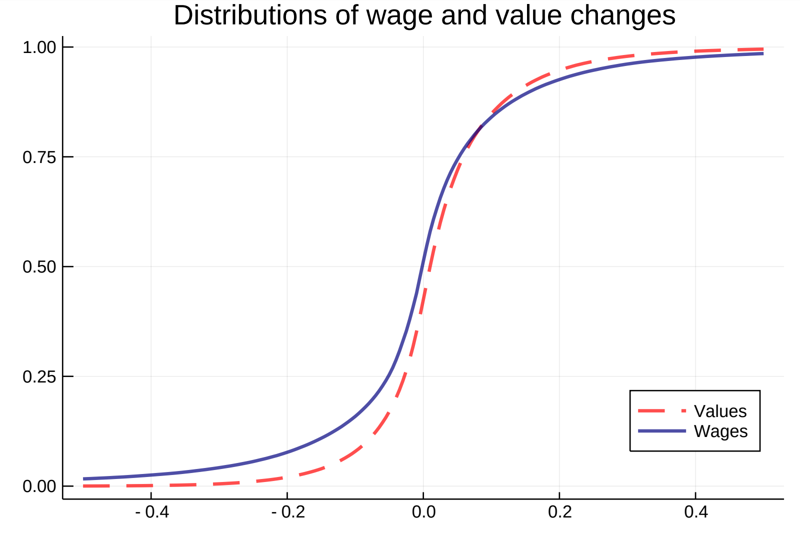


- Incorporating z into the model helps to better match individual wage changes Observed z

Everything else

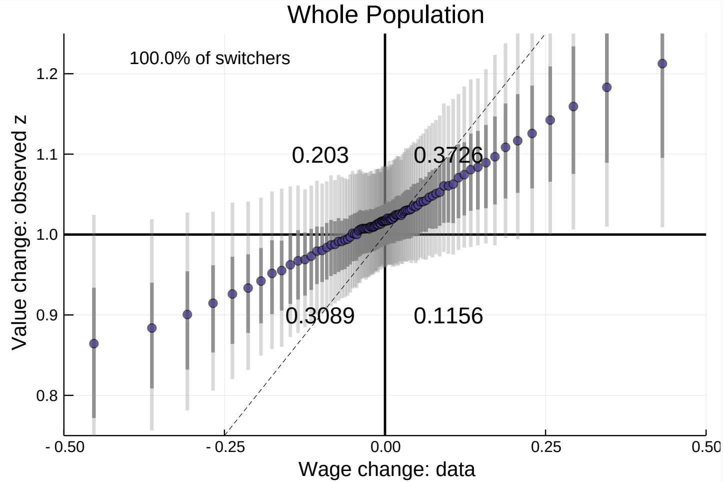
- Transition probabilities: $\lambda_k(a, j, z)$
  - Use observed transitions among the whole set of jobs in the data
  - Workers at better paying jobs or with higher z may be less willing to leave
  - Group a into 3 age bins and z into 4 quartiles
- Distribution of z for UE transitions
  - Comes from variance of z in the data for workers hired out of U
- Distribution of ε
  - Comes directly from variance of wage changes for stayers

Results



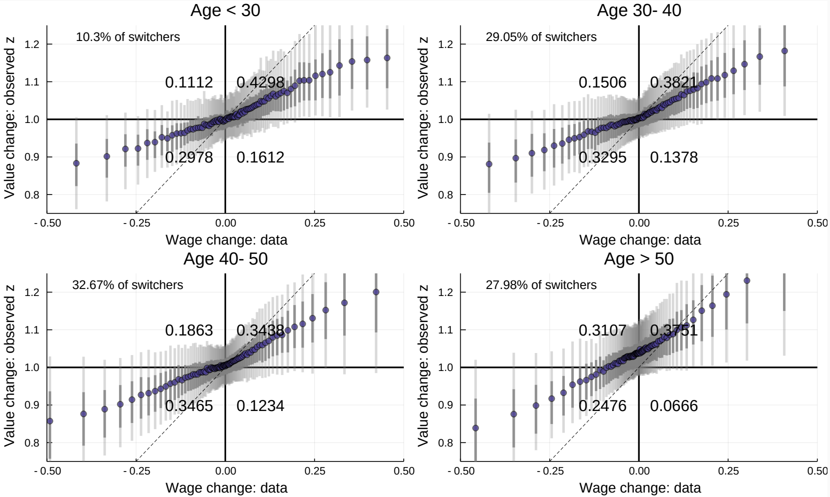
- Value changes smaller in magnitude than wage changes Histograms

Majority of Moves Result in Value Increase



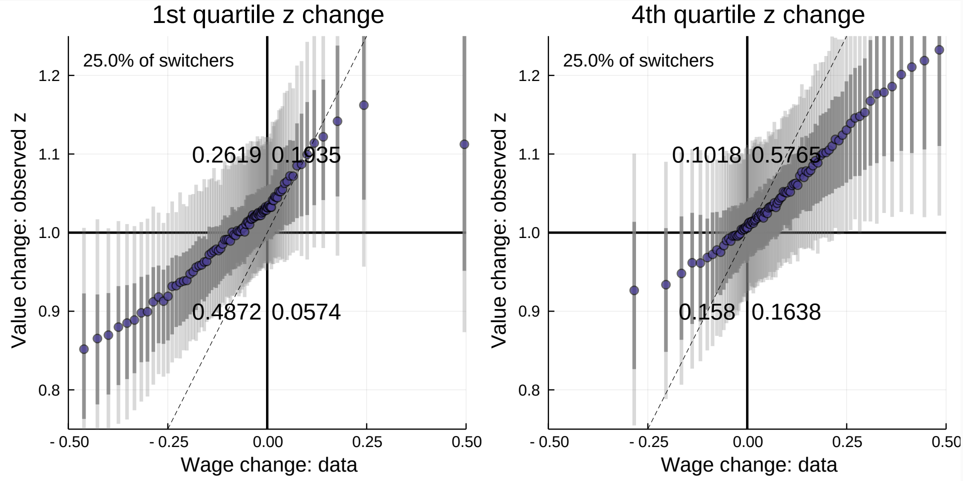
- Pr(value increase | wage cut) = 39.6%; Pr(value cut | wage increase) = 23.8%
- No major differences within fixed worker groups (gender × education) Worker types Tenure Firm/occupation switches

Younger Workers Tend to Increase w; Older Workers Tend to Increase v



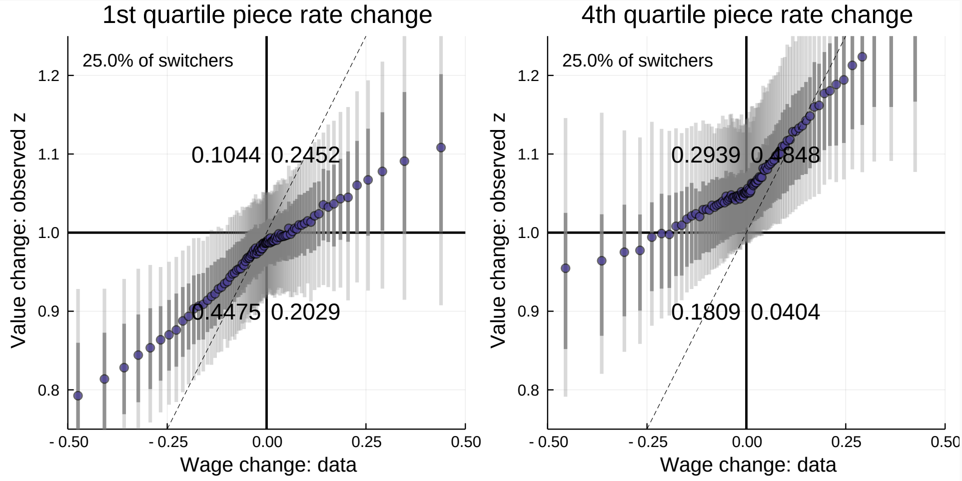
- Younger workers more likely borrowing constrained
- Older workers tend to take more wage cuts that result in higher values

Better Matches Tend to Increase Both Wages and Value



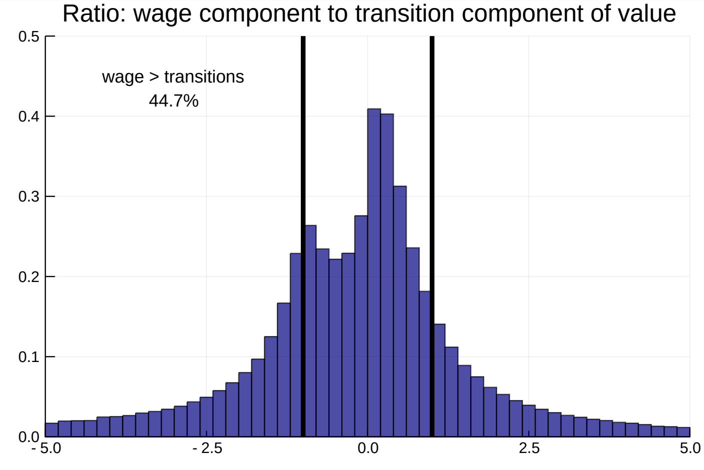
- Increasing z is likely to be good for both wages and values

Still Lots of Wage Cuts for Moves to Higher-Paying Jobs



- In contrast to z, moving up in $\omega(j)$ is more closely tied to increases in *value*
- Piece rate $\neq$ wage $\neq$ value Initial wage Initial omega Initial z

Transition Rates are an Important Component of Value



- Decompose the change in value from (j, z) to (k, z') into 2 components, coming from wages and transition rates
- Value changes come from all different mixes By quadrant

Conclusion and Future Work

- Developed a methodology for assigning values associated with job-to-job transitions
- Findings
  - Careful measurement for documenting features of EE switches
  - Significant mass in all quadrants of wage change/value change plane
  - Unobserved heterogeneity is key for determining values behind each switch
- Next steps
  1. Better understand the motivations behind the transitions
     - Recover distribution of non-wage amenities or reallocation shocks that rationalize negative value switches
     - See if switches coincide with family events, geographic moves, changes in wealth or consumption, etc.
  2. Further develop the model
     - Allow for other forms of worker and job heterogeneity
     - Extend to Postel-Vinay and Robin (2002) setting

Related Literature

Measurement

- Nominal wage changers for *stayers*: Grigsby, Hurst, Yildirmaz (2020)
- Wage changes using administrative data: Kurmann and McEntarfer (2018), Jardim et al. (2019)

Reasons for wage cuts

- Future wage growth, transitions to other jobs: Postel-Vinay and Robin (2002)
- Non-wage amenities: Sorkin (2018), Hall and Mueller (2018)
- “Godfather” shocks: Moscarini and Postel-Vinay (2019) and lots of others

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Type-specific premia $g(i)$

- Let U_{ij} be the number of workers of type i hired into job j from unemployment
- For jobs with $U_{ij} \geq 25$, compute the following:

$$\frac{1}{U_{ij}} \sum_{n=1}^{U_{ij}} \frac{w_n(a_n, j_n, z_n)}{h(a_n)} = \frac{1}{U_{ij}} \sum_{n=1}^{U_{ij}} \frac{\omega(j)h(a)g(i)\mathbb{E}[z]}{h(a)} = \omega(j)g(i) \qquad \forall n : j_n = j$$

- Key: expectation over z is the same as the unconditional, assumed to be 1 for all j
- Set $g(i) = 1$ for baseline group, weighted average of $g(i)\omega(j)$ over j, and compare to weighted average of $\omega(j)$ for baseline group

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WAGE PREMIA $\omega(j)$: FOR JOBS WITH FEWER OBSERVATIONS

1. For jobs with few observations, first compute naive $\tilde{\omega}(j)$ using *all* hires:

$$\tilde{\omega}(j) = \frac{1}{N_j} \sum_{n=1}^{N_j} \frac{w_n(a_n, j_n, z_n)}{h(a_n) g_n}$$

2. For jobs with $U_j \geq 10$ estimate the following:

$$\log \omega(j) = \beta_0 + \beta_1 \log \tilde{\omega}(j) + \beta_2 \mathsf{X}_j + \epsilon_j$$

   X_j contains firm size, occupation, industry

3. Use this relationship to impute a $\omega(j)$ for jobs with less than 10 hires from unemployment

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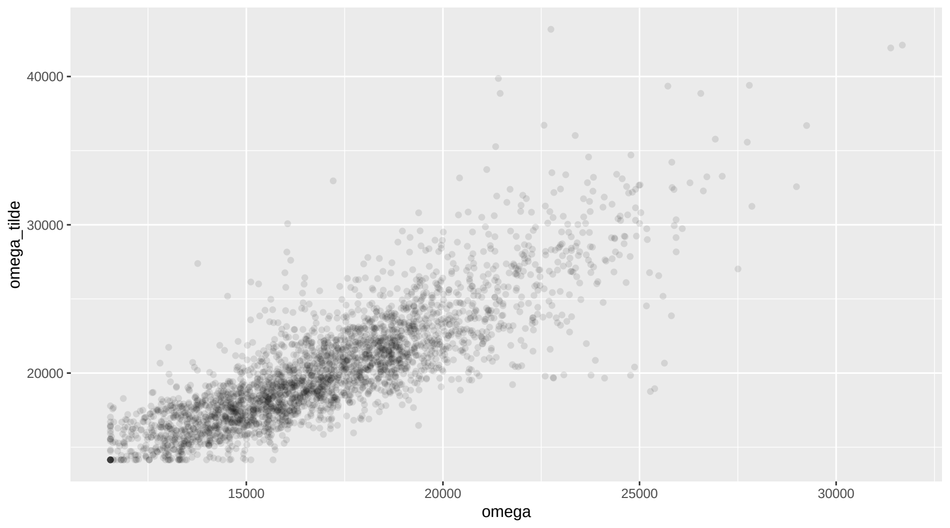
Relationship Between $\omega(j)$ and $\tilde{\omega}(j)$



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EE Wage Change Predictions: With *Observed* Match-Specific Productivity z

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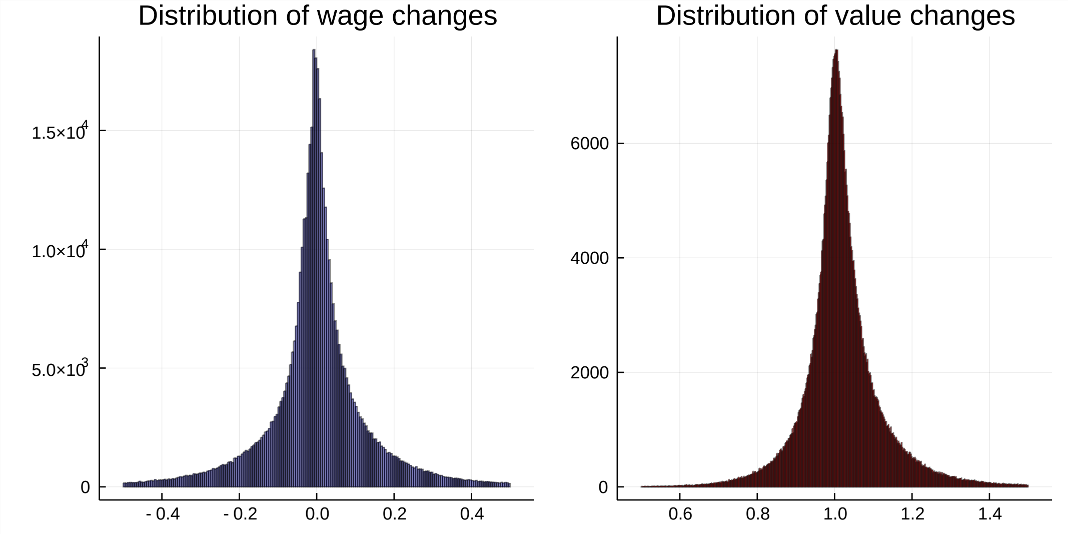
Densities of Wage and Value Changes



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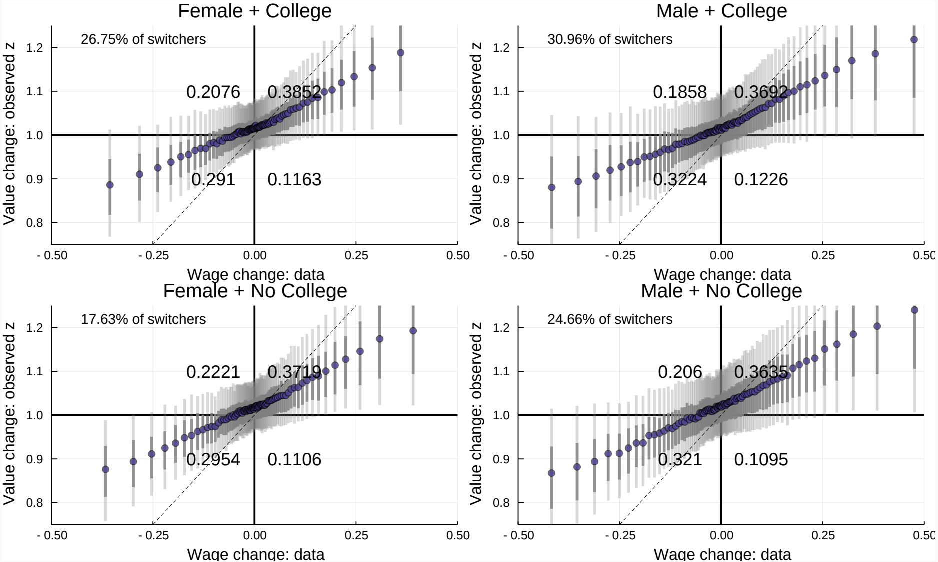
Education × gender



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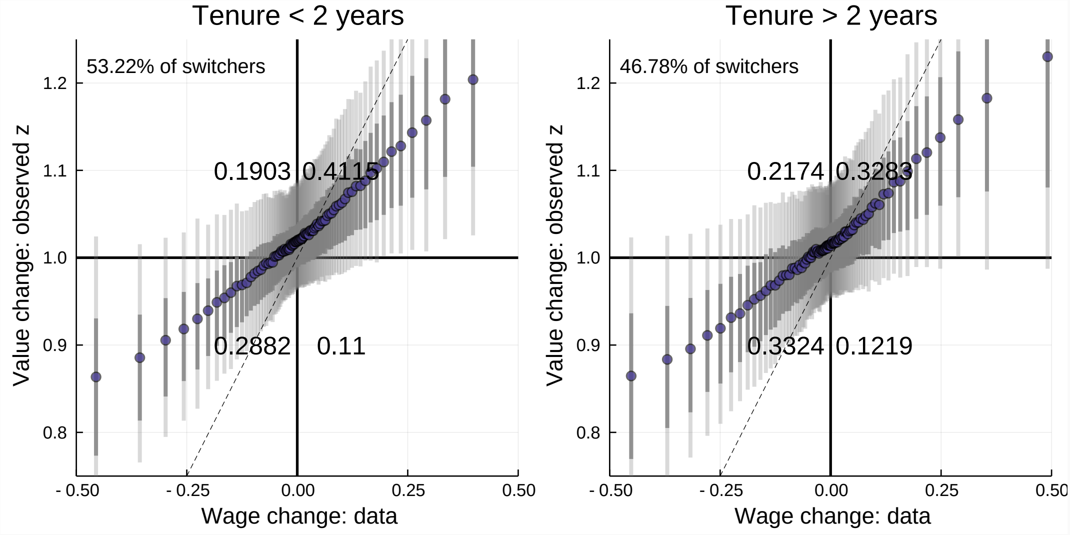
Tenure



Tenure < 2 years
53.22% of switchers
0.1903
0.4115
0.2882
0.11
1.2
1.1
1.0
0.9
0.8
Value change: observed z
- 0.50
- 0.25
0.00
0.25
0.50
Wage change: data
Tenure > 2 years
46.78% of switchers
0.2174
0.3283
0.3324
0.1219
Value change: observed z
Wage change: data

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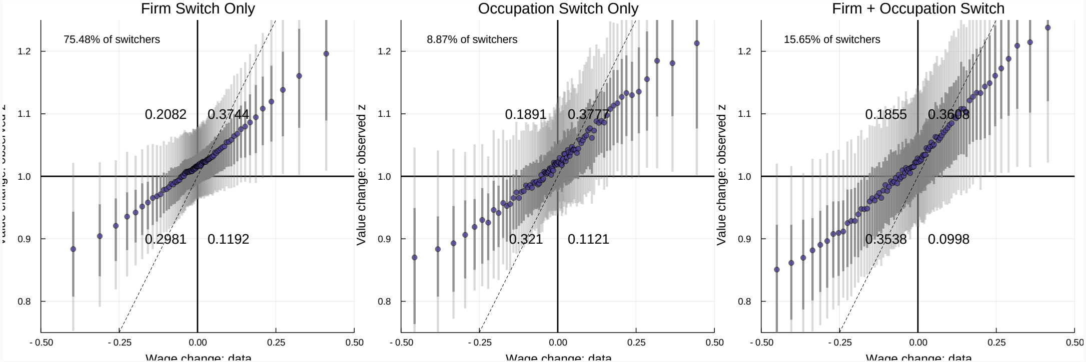
Firm and Occupation Switches



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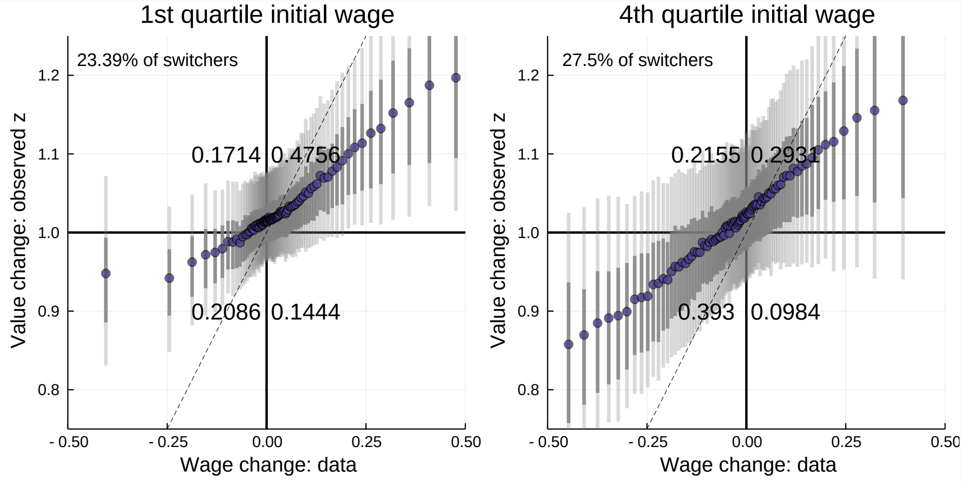
Initial Wage



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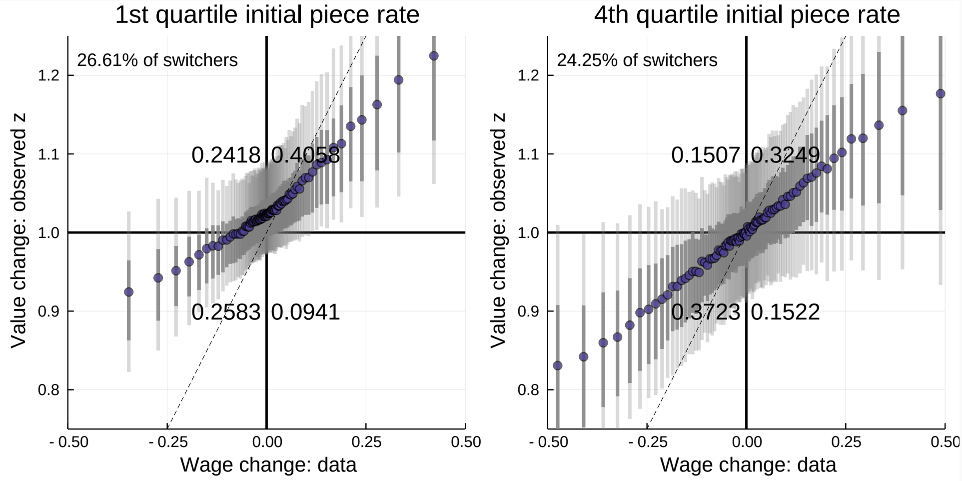
Initial Piece Rate



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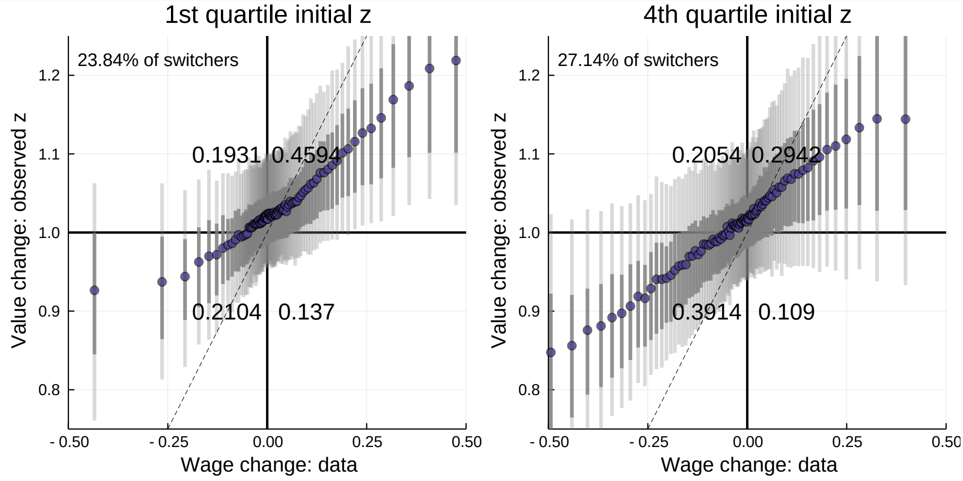
Initial z



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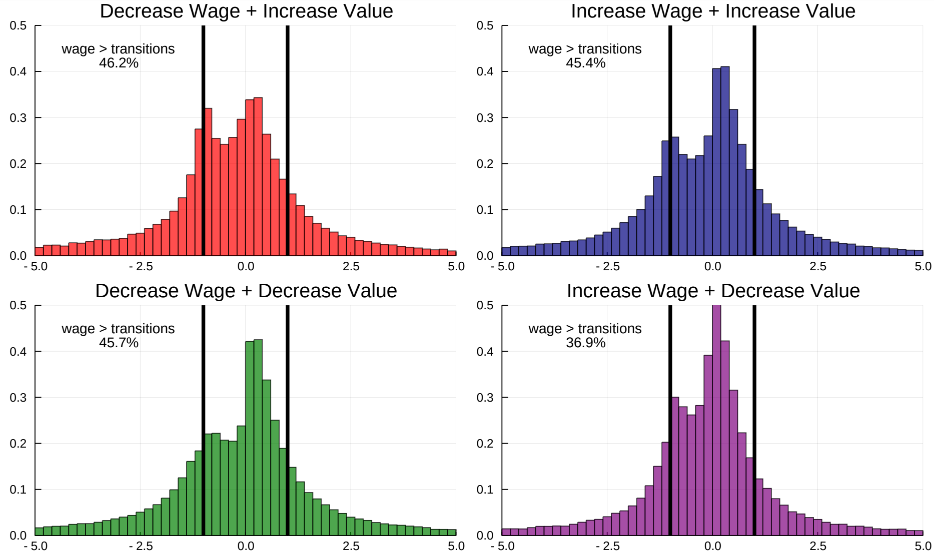
Decomposition by Quadrant



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