Accounting for Job-to-Job Moves: 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

Data

Danish administrative registry data

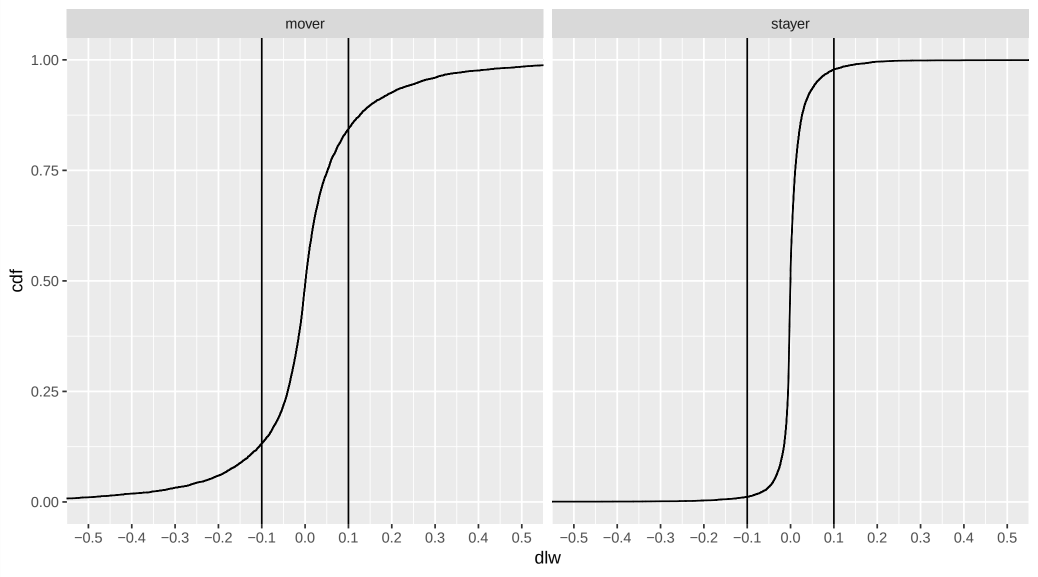
- Entire Danish population from 2008 to 2017
- Monthly payroll records reported by employers
- Total pay each month, firm ID, contractual hours, occupation, industry, demographics,. . .
- Public transfers database for unemployment and OLF states

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

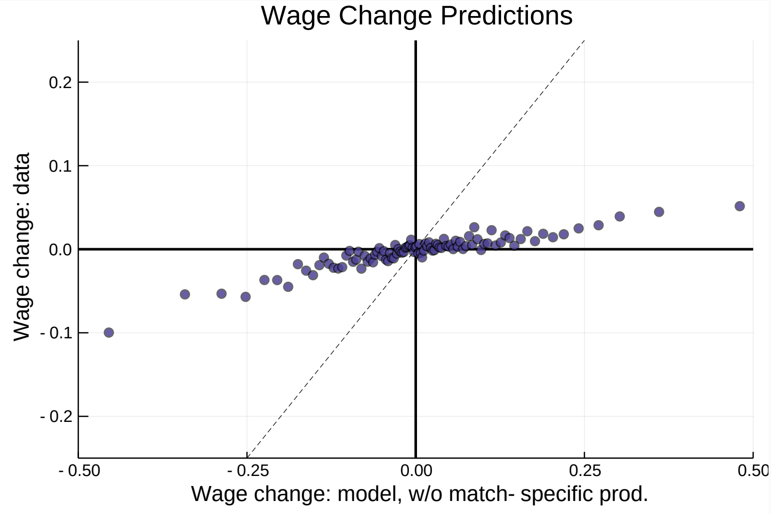
- Match-specific productivity z_n in data:

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

- 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:

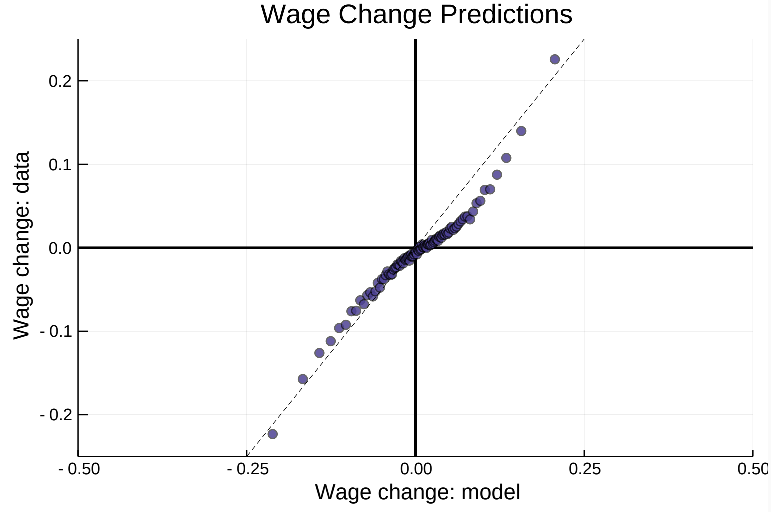
$$\log z_i' = \bar{z} + \rho \log z_i + \beta_1 \log \omega_i + \beta_2 \log \omega_i' + \beta_3 \text{mean}(z|\omega_i) + \beta_4 \text{mean}(z|\omega_i') + \beta_5 \text{var}(z|\omega_i) + \beta_6 \text{var}(z|\omega_i') + \eta_i$$

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



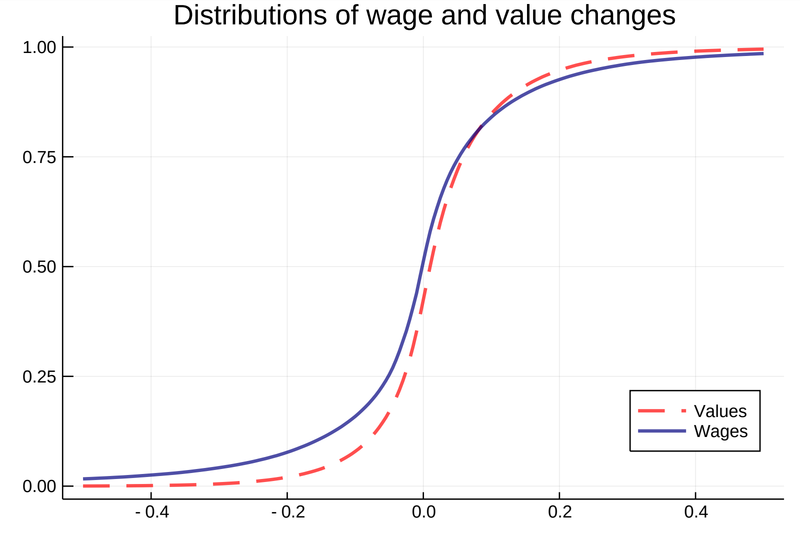
- Incorporating z into the model helps to better match individual wage changes Observed z

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

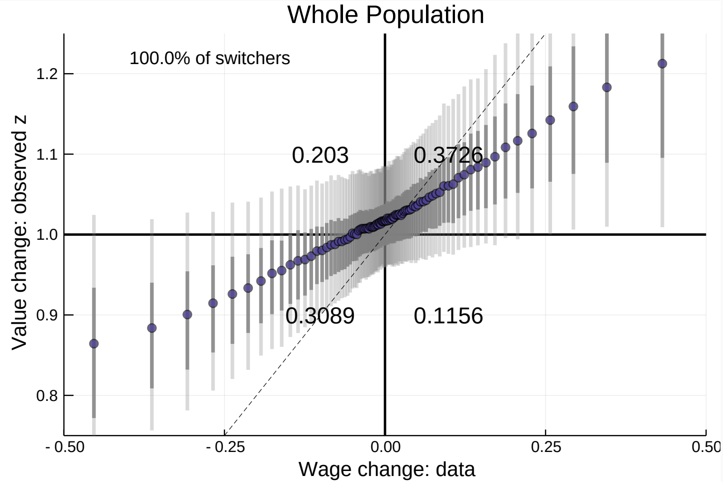
Results

Densities of Wage and Value Changes



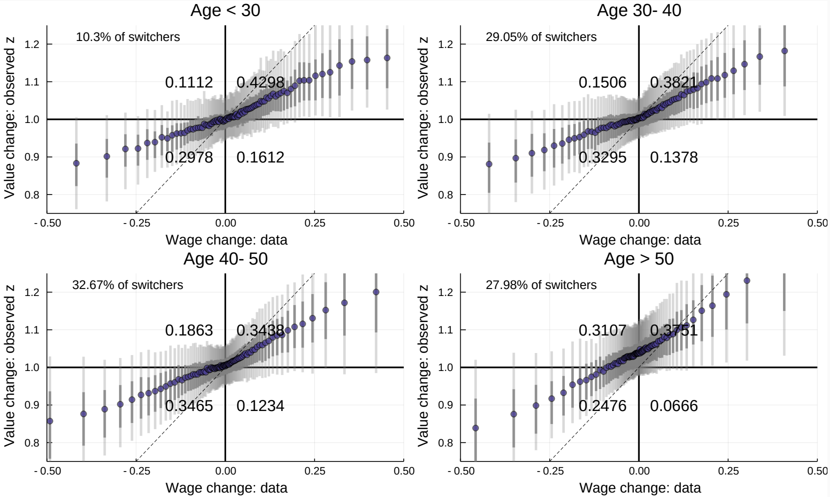
- Value changes smaller in magnitude than wage changes Histograms

Majority of Moves Result in Value Increase



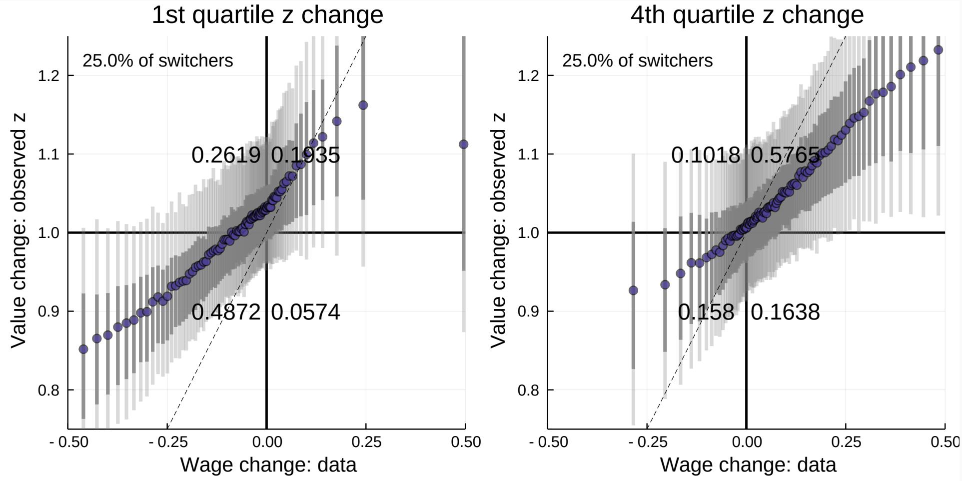
- Pr(value increase | wage cut) = 39.6%; Pr(value cut | wage increase) = 23.8%
- No major differences within fixed worker groups (gender × education) Worker types Tenure Firm/occupation switches

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



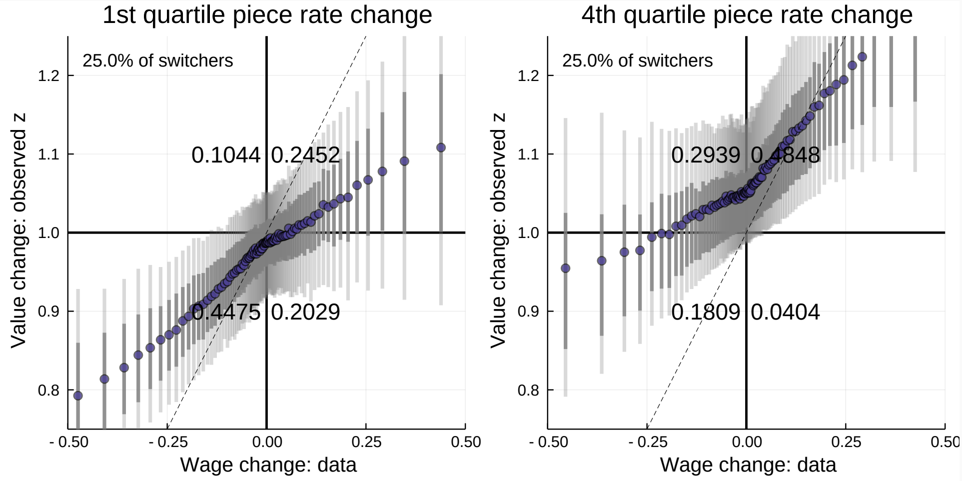
- Younger workers more likely borrowing constrained
- Older workers tend to take more wage cuts that result in higher values

Better Matches Tend to Increase Both Wages and Value



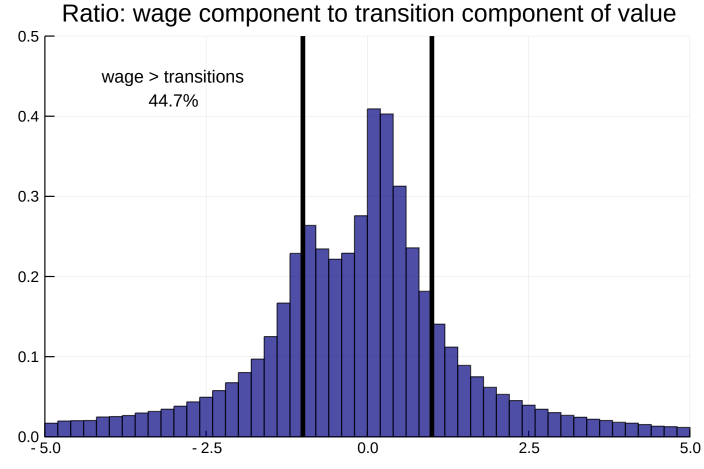
- Increasing z is likely to be good for both wages and values

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

Back

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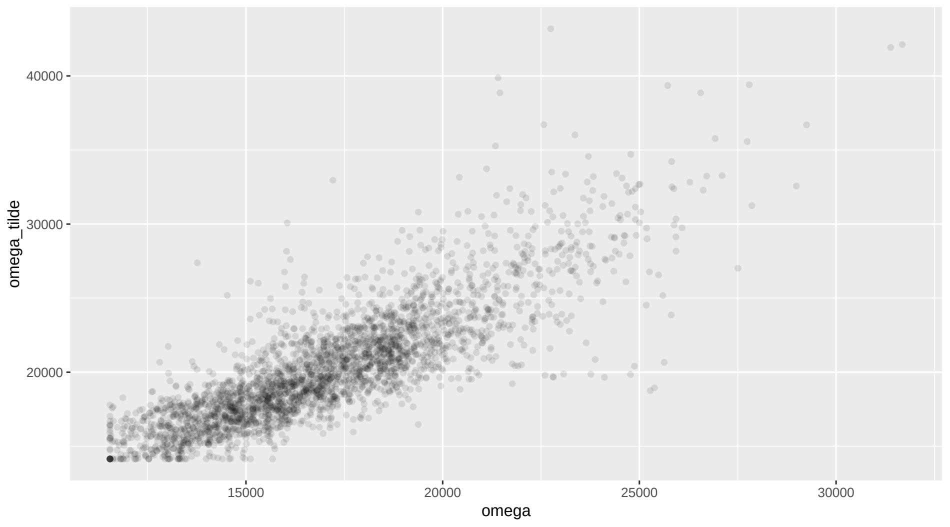
Relationship Between $\omega(j)$ and $\tilde{\omega}(j)$



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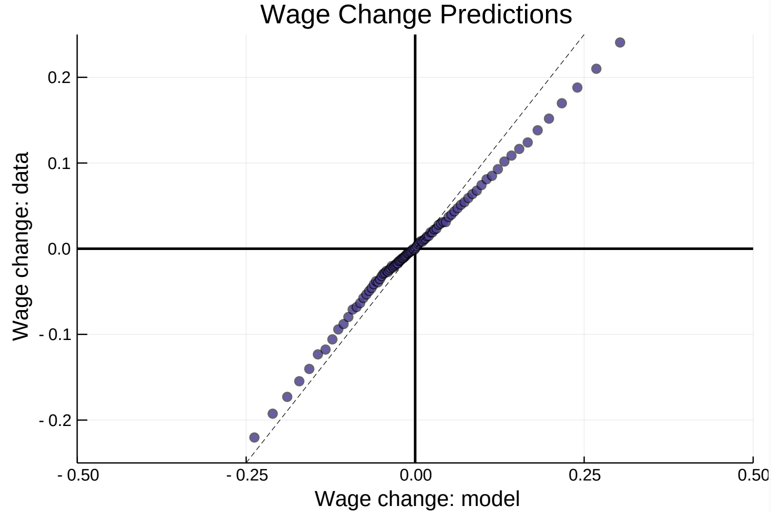
EE Wage Change Predictions: With *Observed* Match-Specific Productivity z



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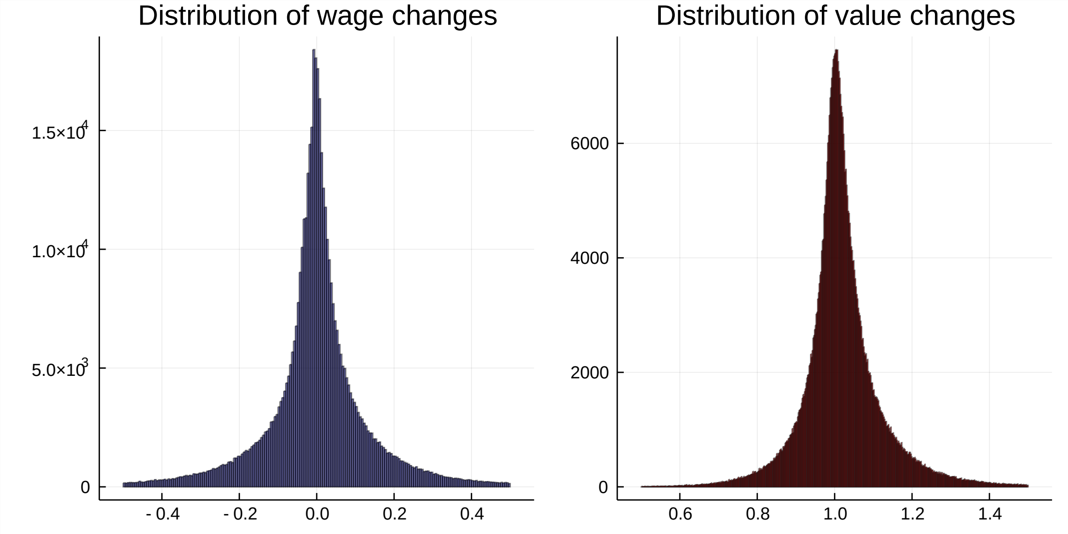
Densities of Wage and Value Changes



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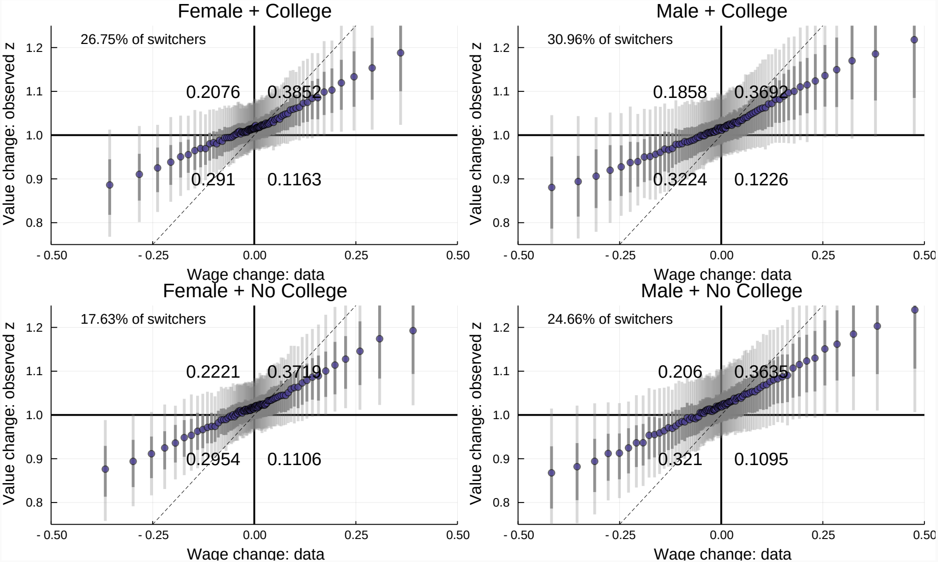
Education × gender



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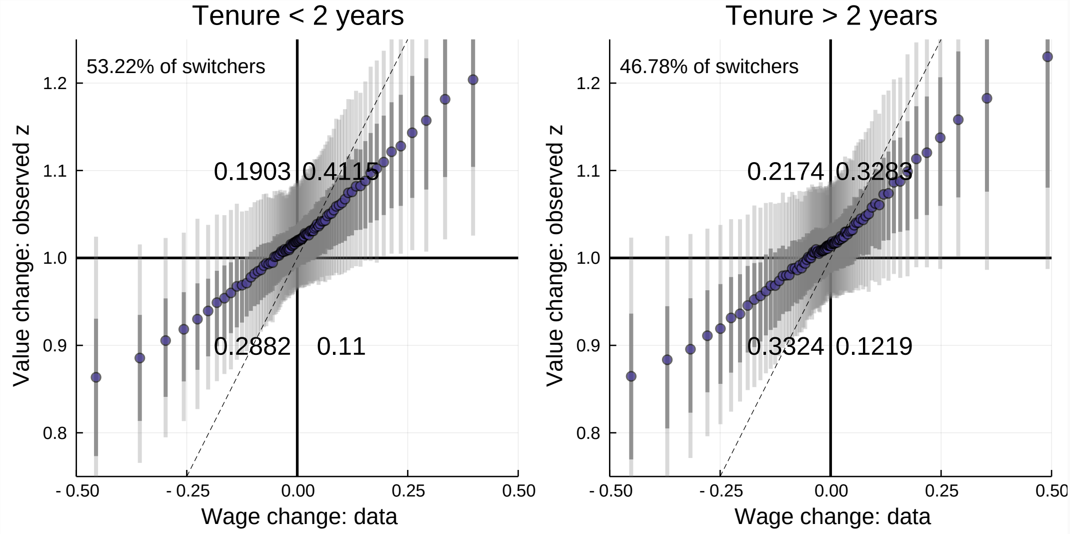
Tenure



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
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

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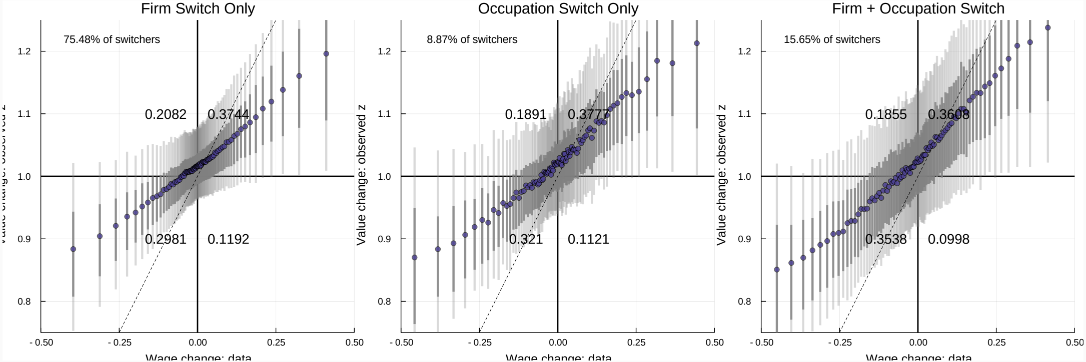
Firm and Occupation Switches



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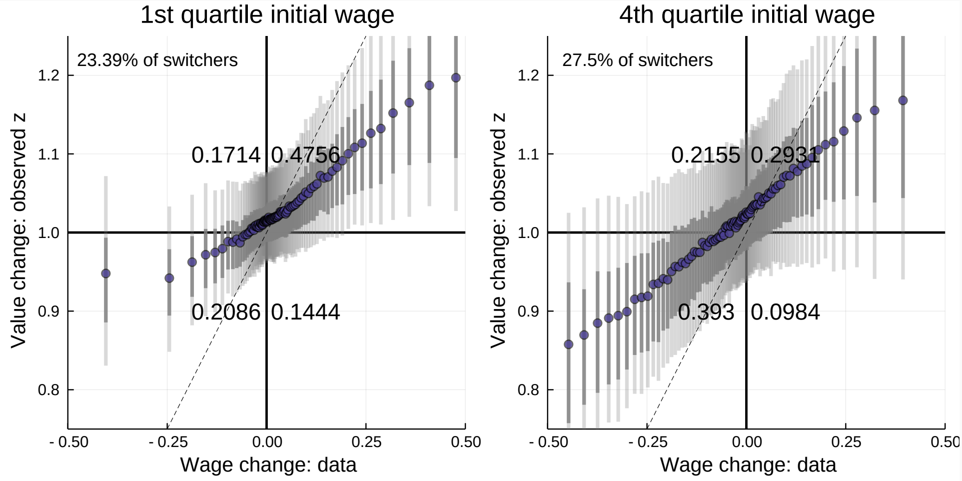
Initial Wage



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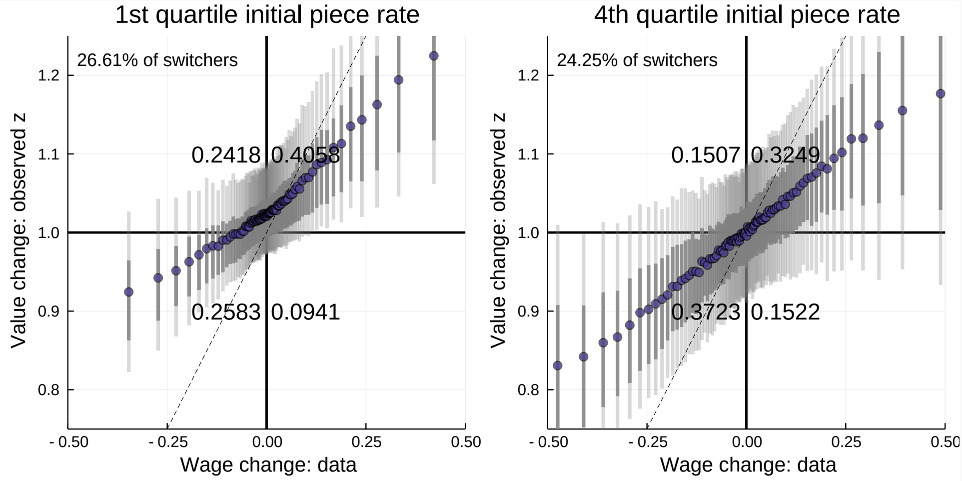
Initial Piece Rate



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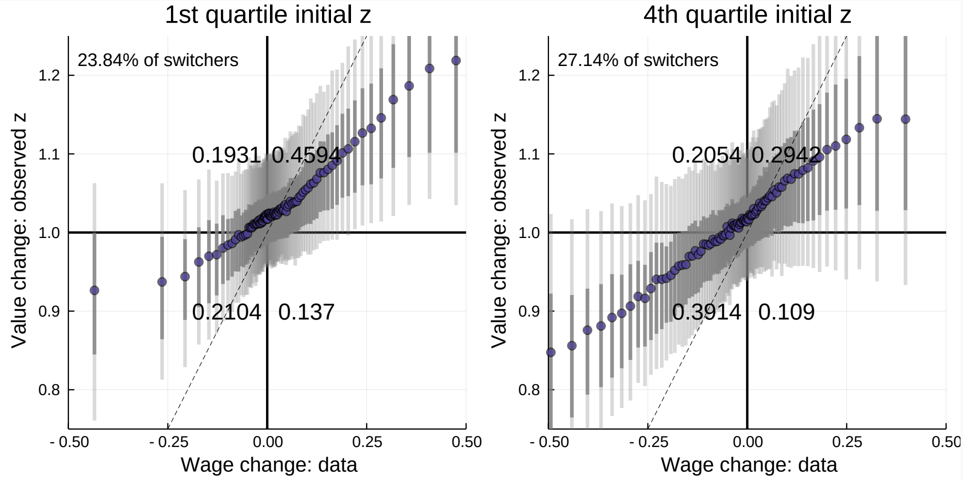
Initial z



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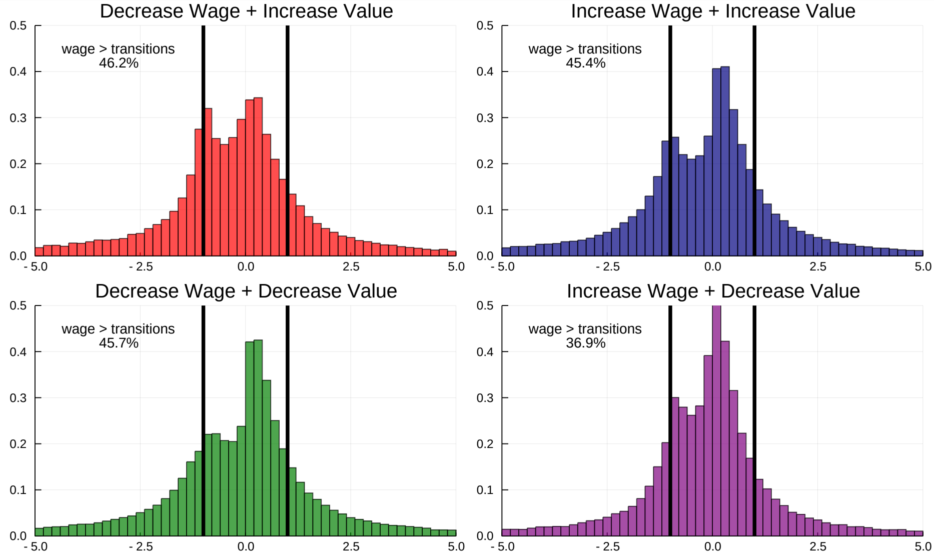
Decomposition by Quadrant



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