# Changing Jobs to Fight Inflation: Labor Market Reactions to Inflationary Shocks

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**Abstract:** Recent empirical work shows a strong positive correlation between job-to-job transition rates and nominal wage growth in the U.S. First, using time series regressions, structural monetary policy shocks, and survey data on search effort we provide evidence that inflationary shocks cause higher job-to-job transitions in the subsequent years. Second, to understand the aggregate implications, we build a structural model with aggregate shocks and competitive on-the-job search in which wages react sluggishly to inflation. In periods with high inflation, the decline in real wages incentivizes the employees to search on-the-job more actively, to negotiate a new contract, but also to be less selective in their search behavior. This creates a fundamental trade-off: increased search effort leads to more job-to-job transitions while being less selective reduces the expected efficiency gain in each transition. Therefore, the effect on output becomes ambiguous. Third, we calibrate the model to the U.S. economy and confirm that the output response to inflation shock is non-monotonic. Importantly, our paper highlights a novel role for inflation: the monetary authority can stimulate productivity with an inflationary shock through job-to-job transitions.

***** PRELIMINARY AND INCOMPLETE DRAFT *****

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# 1 Introduction

Since job switches are usually associated with wage and productivity increases[1], the speed at which employees change employers is considered a measure of the health of the economy. Understanding what drives differences in job-to-job transitions across time and countries can be crucial for improving economic performance. In this paper, we identify a novel policy tool that affects the rate of job-to-job transitions: monetary policy. When wages are not indexed to inflation[2], workers' real wages decrease at a faster rate in periods with unexpectedly high inflation. Therefore, potential gains from being able to renegotiate wages are higher for workers. Workers could respond to a positive inflationary shock by (1) increasing their search effort, thus, making it more likely that they will receive a job offer and (2) being less selective, i.e., accepting lower wage offers which lead to less productive matches. The first channel (search effort, henceforth) increases the number of job transitions, while the extent to which these transitions lead to more productive matches depends on the size of the second channel (selectivity, henceforth). Hence, the impact of inflation shocks on output is ambiguous and potentially depends on the size of the shock.

We measure how unexpected inflation affects aggregate productivity through its impact on the job search behavior of workers. We first utilize reduced-form causal inference to argue a quantitatively meaningful change in the rate of job switches following inflation shocks. We find that a 1% decline in real wages due to an unexpected inflation shock leads to a 7 percentage points increase in the probability of receiving a job offer in the following six-month period. To understand the resulting change in productivity, we build a model of directed on-the-job search with aggregate shocks. We calibrate the model to match the empirical job switching patterns and associated wage increases. The calibrated model suggests a non-monotonic output response following inflation shocks, suggesting both channels (search effort and selectivity) are quantitatively meaningful.

Although unexpected inflation movements have been relatively small for the U.S., they can imply a large drop in real wages once accumulated. Figure 1 summarizes this idea. The black line represents the discrepancy between Survey of Professional Forecasters (SPF) 1-year ahead inflation forecast versus the realized inflation. The red (green) line represents what fraction of

[1]See e.g. Fallick and Fleischman (2004), Christensen et al. (2005) and Jolivet et al. (2006). Under a large variety of theoretical models, job changes come with changes in both wage and productivity (See Postel-Vinay and Robin (2002) and Menzio and Shi (2011)).

[2]Existence of nominal frictions in wage setting has long been documented. See Appendix B for a broad overview of the evidence regarding the extent of wage indexation.

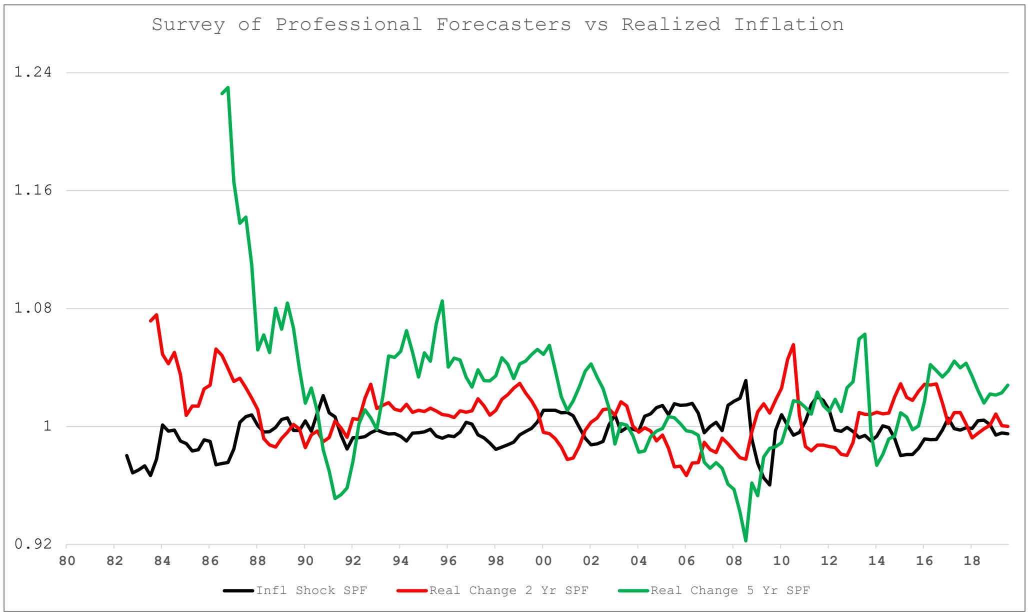


Figure 1: The Discrepancy Between the SPF Forecast and Realized Inflation The x axis refers to the calendar year. The black line represents the difference between the 1-year ahead SPF forecast and the realized inflation. The values above 1 indicate inflation exceeded forecasts. The red line represents the cumulative real wage loss for a worker who signed his contract two years ago, based on SPF forecasts. The green line represents the cumulative real wage loss for a worker who signed his contract five years ago, based on SPF forecasts.

the intended real wage is received by a worker who signed a contract 2 (5) years ago based on SPF forecasts. The real wage losses can be as high as 8%, and gains can be as high as 16% for some workers[3] even though the surprise inflation never exceeds 6% and is mostly below 3% in magnitude. Hence, the output response can be large once small inflation shocks accumulate.

Our paper is motivated by the recent finding by Moscarini and Postel-Vinay (2017) and Karahan et al. (2017) that once job-to-job transition rates are controlled for, unemployment-to-employment transition rates have little to no predictive power on nominal wage growth. On the other hand, the job-to-job transition rate and nominal wage growth have a large significant positive correlation. This is at odds with the classical Philips Curve idea where low unemployment strengthens workers' bargaining position and puts upward pressure on wages. It rather suggests the real threat point of the workers being switching to another job, that is, firms are more likely to increase wages when job-to-job transitions are more likely. Our analysis confirms the co-movement between job-to-job transitions and the inflation rate. Acknowledging that both objects are equilibrium outcomes, we try to unpack which shocks might be behind the positive correlation and the

[3]See Appendix Figure 10 for the same plot with the Michigan Consumer Survey inflation forecasts.

aggregate implications of the connection between the two.

In the first half of the paper, we provide three main pieces of empirical evidence that suggests the positive correlation between inflation and the job-to-job transition rate is driven by the positive effect of the former on the latter, rather than the other way around. First, we run Granger Causality tests on the aggregate data as well as panel regressions across U.S. regions and states. While inflation helps predict future job-to-job transition rates, job-to-job transitions do not help predict future inflation movements. Second, we use the previous estimates of structural monetary policy shocks instead of inflation in our regressions. This analysis allows us to look beyond the reverse causality argument, as these shocks are arguably exogenous to the economic conditions. Our results suggest that an unexpected one percent decrease in nominal interest rates can bring an increase in the job-to-job transition rates up to 0.4% percent. Third, we provide some direct evidence on the mechanism using individual-level survey data on on-the-job search behavior. We find that a cumulative wage loss of 1% due to unexpectedly high inflation increases the likelihood of receiving an offer by 7 percentage points and the expected number of offers by 0.17 in a six-month period.

In the second half, we build a model of competitive on-the-job search with endogenous search effort where the contract space is restricted to nominal wage contracts. The environment involves aggregate shocks to productivity where the agents form rational expectations. In the model, the agents respond to an unexpected positive inflation shock by increasing their search effort, as the option value of search increases[4]. Simultaneously, the agents also respond by searching in markets with lower posted wages as their current situation becomes more desperate. Hence, they trade a higher wage for a higher probability of finding a new job. The increased search effort leads to more frequent job-to-job transitions, which, by itself, would increase average productivity. However, the reduced asking wage makes these transitions less productivity-enhancing, therefore creates a force that decreases average productivity. In short, inflationary shocks unambiguously increase job-to-job transitions while their effect on productivity is undetermined. A preliminary calibration of the model to the U.S. economy confirms the non-monotone response of the output. When the unexpected increase in inflation is bigger than a threshold value, the selectivity channel starts to dominate, and the output decreases.

[4]See e.g., Christensen et al. (2005) and Mueller (2010) for evidence on job search effort decreasing as workers move up the job ladder.

The proposed mechanism has important implications. First, it explains how output response may not be monotonic in the size of the inflation shock. Thus, it provides a bridge between seemingly disparate estimates of the literature on the real effects of monetary policy shocks[5]. Second, it provides a novel mechanism on how monetary policy can affect the real economy in the short run. Through monetary policy shocks, the monetary authority can improve the allocation of labor in the economy, thus increase productivity. Third, it provides a novel channel that can explain why some recessions are associated with a more pronounced 'cleansing' effect than the others. In our model, the sign and the magnitude of the unexpected price movement can affect both the speed and the effectiveness of job reallocation during the recession.

This paper is closely related to the literature that analyzes the interaction between inflation and the efficiency of labor markets. In particular, the idea that inflation helps reduce labor market frictions and increase productivity was first proposed by Tobin (1995) and tested by Card and Hyslop (1997). In this channel, nominal downward wage rigidity can be made non-binding with a positive inflation rate that ensures nominal rigidity doesn't translate to a real rigidity[6]. Our model incorporates this benefit of inflation, on top of our novel channel, that it incentivizes job switches. The most closely related work to ours is by Moscarini and Postel-Vinay (2019) (MPV henceforth), who incorporate a random on-the-job search framework into a New Keynesian DSGE model. When job-to-job transition rates are high, employees receive more offers, some of which are matched by the incumbent firm. Matched offers are essentially cost shocks to the firm and it responds by raising prices. Hence, a higher than average job-to-job transition rate brings higher than average price inflation. The mechanism in MPV and ours are complementary. MPV shows how a labor demand shock brings wage inflation and therefore price inflation. We show how a shock to price inflation increases job-to-job transitions. Thus, our contribution is three-fold. First, our mechanism, in combination with theirs, explains how labor demand shocks can be amplified through a combination of offer matching and changing search behavior. Second, shocks to price inflation can also trigger this cycle. Third, the monetary policy recommendations could change [7]. because the monetary authority needs to consider the job switching response to predict the

[5]See Wolf (2019) for an overview of these findings.

[6]Lunnemann and Wintr (2010) find real wage rigidity is indeed more substantial in Luxembourg where there is a state-imposed automatic wage indexation.

[7]Tom Fairless of the Wall Street Journal, in his article based on the results by MPV, argues "If workers are less willing to switch jobs, central banks could press harder on the gas pedal to stimulate the economy without worrying about inflation. And there may be little policy-makers can do to influ-

response of the real economy. MPV assumes on-the-job search effort is fixed, hence shuts down our channel by assumption[8]. The empirical evidence in Section 2 favors our channel if one or the other has to be picked.

This paper also contributes to the literature on the efficiency of job reallocation. This literature asks when reallocation is productivity-enhancing and when it is not. A broad finding is that U.S. recessions were accompanied with productivity-enhancing job reallocation until the great recession[9] while the reallocation during the great recession was both slower and less productivity-enhancing (Mukoyama (2014) and Foster et al. (2016)). Haltiwanger et al. (2018) asks whether the decline is due to a decreased number of transitions or a smaller productivity gain conditional on making a transition and find most of the decline comes from the latter. Caballero and Hammour (1994) discusses potential frictions that may create inefficient job reallocation during recessions. Barlevy (2003) emphasizes increased credit market frictions while Ouyang (2009) suggests early exits as mechanisms large enough to reverse the 'cleansing' effect of the recessions[10]. Gautier et al. (2010), in a model with on-the-job search, analyzes which wage-setting mechanisms generate socially efficient job switches. They conclude, for social efficiency, the hiring premium (to induce the worker to undertake search) should equal the no-quit premium (to prevent the worker from making a job switch later) which happens in wage posting with commitment but not in wage bargaining or the sequential auctions of Postel-Vinay and Robin (2002). The competitive search framework we use also satisfies the efficiency requirement posited here; the inefficient switches in our setting are purely due to nominal frictions. The closest papers to ours in this literature are by Moscarini (2001) and Barlevy (2002). Moscarini (2001) considers a trade-off similar to ours. In his model, similar to the competitive search models, workers decide between a good match with

ence the job-switching rate except to watch it." (2019, Nov 17 `https://www.wsj.com/articles/one-explanation-for-weak-wage-growth-workers-reluctance-to-switch-jobs-11573999201?shareToken=st5a849d04f72440fca240048db4bad6d1`). Our mechanism suggests there is a direct link from monetary policy shocks to job-to-job transition rates.

[8]Incorporating the search effort channel in their model is not trivial. In MPV, only the distribution of productivities across jobs is a state variable while adding the search effort makes the joint distribution of wages and productivities a state variable. The surplus function is not sufficient to characterize the transitions either because the search effort choice is not efficient due to the restricted contract space. Hence, the tricks in Lise and Robin (2017) cannot be used to simplify the problem. Our model avoids this issue by utilizing the block-recursivity of competitive search where the distributions are no longer state variables. We present a version of our model under random search in Appendix **??**

[9]See e.g. Davis and Haltiwanger (1992), Caballero and Hammour (1994), Davis et al. (2006) and (Davis et al., 2012).

[10]Foster et al. (2008) shows if pricing decisions are not taken into account, the effect of demand and productivity shocks on profitability can be confounded. Thus, the reallocation that is only profitability enhancing can be mislabeled as productivity-enhancing.

a long queue and a mediocre match with a short queue. Thus, in tight labor markets, the initial matches are of higher quality and the reallocation is slow. Barlevy (2002) shows decreasing job-to-job transitions during recessions can generate an effect large enough to offset the 'cleansing' effect of recessions. In his model, after a bad productivity shock, firms post fewer vacancies, which reduces the rate of job-to-job transitions, thus the productive reallocation of workers in the economy. In contrast, our model focuses on the effect of the inflationary shocks and generates productivity drops even when the reallocation rate is higher.

Lastly, our mechanism is also related to the literature that analyzes how the extent of wage flexibility affects the output response to monetary policy shocks. Olivei and Tenreyro (2007) shows that the effects of monetary policy shocks depend on their timing during the year, and it is consistent with the fact that a significant fraction of firms renegotiate wage contracts at the end of the year. Björklund et al. (2019) find that the output response to monetary policy is bigger in periods where a larger fraction of wage contracts are nominally fixed, using a micro-level dataset on details of collective wage agreements in Sweeden[11].

We proceed with the description of the data used. Section 2 provides the empirical analysis. Section 3 lays down the model and provides the theoretical results. Quantitative results of the model are presented in Section 4.

## 2 Empirical Analysis

This section presents three types of evidence to argue that the positive correlation between inflation and job-to-job transitions stems from the causal effect of inflation on job-to-job transitions. First, subsection 4.1 uses the time-series structure of the data to show that a high inflation today predicts a high job-to-job transition rate in the future. In contrast, a high job-to-job transition rate today does not predict high inflation in the future. For this aim, both Vector Auto Regressions with aggregate data and panel regressions with state level data are used. Second, subsection 2.2 uses popular estimates of structural Monetary Policy shocks to get a causal estimate of the effect of inflation on job-to-job transitions and confirms that higher inflation causes higher job-to-job transitions. Third, subsection 2.3 provides direct evidence on how inflation increases the job search effort of the employed from survey data. We later use the estimates from this subsection to disci-

[11]See also Benabou (1992) and Diamond (1993) for how inflation affects search effort in product markets.

pline the macro model.

## 2.1 Predictive Regressions

This subsection presents findings from three datasets: (1) national monthly job-to-job transition and inflation series between 1995-2018, (2) national yearly series between 1976-2018, and (3) quarterly state-level series between 2000-2018. All three analyses use different periods due to data limitations but support the same argument: higher inflation predicts higher job-to-job transitions in the future, while higher job-to-job transitions do not predict higher inflation.

Following Moscarini and Postel-Vinay (2019), we will use a variable called 'acceptance rate' as introduced therein. This variable is the ratio of the job-to-job transition rate to the unemployment-to-employment transition rate. The division is to ensure that employees' willingness to switch jobs is isolated from job availability, which moves both rates simultaneously. The 'acceptance rate' is a natural candidate for what our mechanism is about; higher inflation affects job-to-job transitions by changing the employees' willingness to switch[12].

The other primary variable we construct is called 'inflation mistake' and defined as the discrepancy between the expected and the realized inflation for a one-year period. At a time $t$, this measures the accumulated unexpected prices moves since time $t-1$.

### 2.1.1 Monthly Analysis, Nation Level

In this section, we use the series made available by Fujita et al. (2019)[13] that covers the period from September 1995 to December 2018 for the monthly job-to-job transition rates. Over-the-year log changes in the Consumer Price Index (CPI) provide price inflation. Inflation expectations are taken from the University of Michigan Survey of Consumers. We take logs of all labor market variables, and HP filter all variables with a smoothing parameter of $8.1 \times 10^6$ as in Moscarini and Postel-Vinay (2019).

Table 3 presents the results from Granger Causality tests between the 'acceptance rate' and price inflation from a simple Vector-Auto-Regression (VAR) analysis with 12 lags. The Granger

[12] In MPV, the acceptance rate is primarily determined by the position of the workforce in the job ladder. Since the search effort of the employed is not a choice, and the switches are exogenous, no other model component can affect the acceptance rate once conditioned on the distribution of workers across jobs.

[13] See Appendix A for details on the data sources used throughout the empirical analysis.

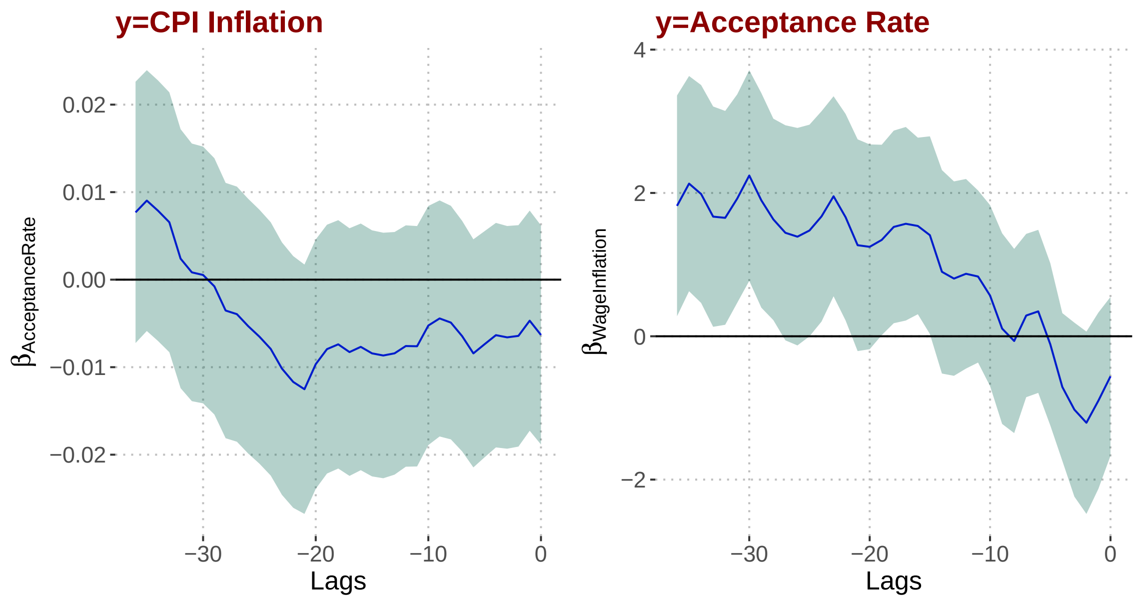


Figure 2: The left panel presents the coefficient estimates and the associated 95% CI for $\beta$ where price inflation is regressed on the 'acceptance rate' with the specification in Equation 1. Each point corresponds to an estimate where the associated lag is in the x-axis. The right panel provides the same plot where the 'acceptance rate' is regressed on the price inflation. See Appendix A for details of the data sources.

Causality test rejects if the lags of variable $x$ help predict variable $y$ above and beyond the lags of variable $y$. The results indicate that inflation Granger-causes job-to-job transition rates with 5% significance, while the other direction shows no predictive relationship.

We continue by replicating the analysis inMoscarini and Postel-Vinay (2019) that questions and rejects a price Philips curve. Specifically, we run OLS regressions of the form:

$$y_t = \beta x_{t-L} + \gamma Z_{t-L} + \epsilon_t \tag{1}$$

Firstly, we set the price inflation as $y$ and the acceptance rate as $x$ and then switch their places. The unemployment rate and unemployment-to-employment transition rate constitute $Z$ in both types of regressions. We vary $L$ from 0 to 36 months and analyze how $\beta$ changes. Figure 2 presents the results of this analysis. The left panel indicates no significant relationship between the lags of the acceptance rate and the CPI inflation, where most of the estimates up to 2,5 years are negative. On the other hand, as shown in the right panel, a higher CPI inflation predicts a higher 'acceptance rate' 15 to 36 months after[14].

[14]Potential causal channels in either direction would take some time to show up in the data. In our mechanism, workers need to realize the real wage changes and manage to find a job after increasing their search effort before a

### 2.1.2 Quarterly Analysis, State Level

Here we utilize the Longitudinal Employer Household Dynamics (LEHD) data set by the U.S. Census. The LEHD provides publicly available job-to-job transition rates in quarterly frequency at the state level starting from 2000. This structure allows using the state-level variation in prices and job-to-job transitions[15]. Unfortunately, the state-level inflation data is only available in yearly frequency and starts from 2008[16]. Therefore, we use state-level wage inflation data from the Quarterly Census of Employment and Wages (QCEW) as a proxy. We take logs and four-quarter trailing moving averages of all labor market variables, and HP filter all variables with a smoothing parameter of $10^5$ as in Moscarini and Postel-Vinay (2019). We then combine all the data and run OLS regressions of the form:

$$y_it = \beta x_{it-L} + \gamma y_{it-L} + \upsilon_i + \nu_t \epsilon_i t \quad (2)$$

where we analyze the lead-lag relationship between the wage inflation and the 'acceptance rate'[17]. $\upsilon_i$ and $\nu_t$ denote the state and time fixed effects. The results are in Figure 3. Our mechanism would be able to explain both panels. The search effort channel would suggest wage inflation be a positive predictor of the 'acceptance rate' through its effect on price inflation. On the other hand, the job ladder channel, which is first proposed by MPV, would suggest the 'acceptance rate' be a negative predictor of wage inflation. If the 'acceptance rate' is high, workers are at the bottom of the ladder, and switches come with small wage improvements.

## 2.2 Structural Monetary Policy Shocks

Although the results in Section 4.1 are suggestive, they do not prove any causal relationship between inflation and job-to-job transitions. Here, we use structural estimates of monetary policy shocks as exogenous proxies for the inflation level. Our mechanism would imply a negative relationship with nominal interest rate shocks and job-to-job transitions.

change in job-to-job transition numbers can be observed. Similarly, under the classical menu cost assumptions, the mechanism argued by Moscarini and Postel-Vinay (2019) requires firms to adjust their prices after their labor costs go up.

[15]CPS, which is monthly, provides information regarding the location of the participant. However, once the sample is divided into job switchers across states, the sample size becomes an issue.

[16]See Personal Consumption Expenditures (PCE) by State in https://apps.bea.gov/regional/downloadzip.cfm.

[17]The results are robust to removing the fixed-effects or $y_{it-L}$ from the right-hand side of (2).

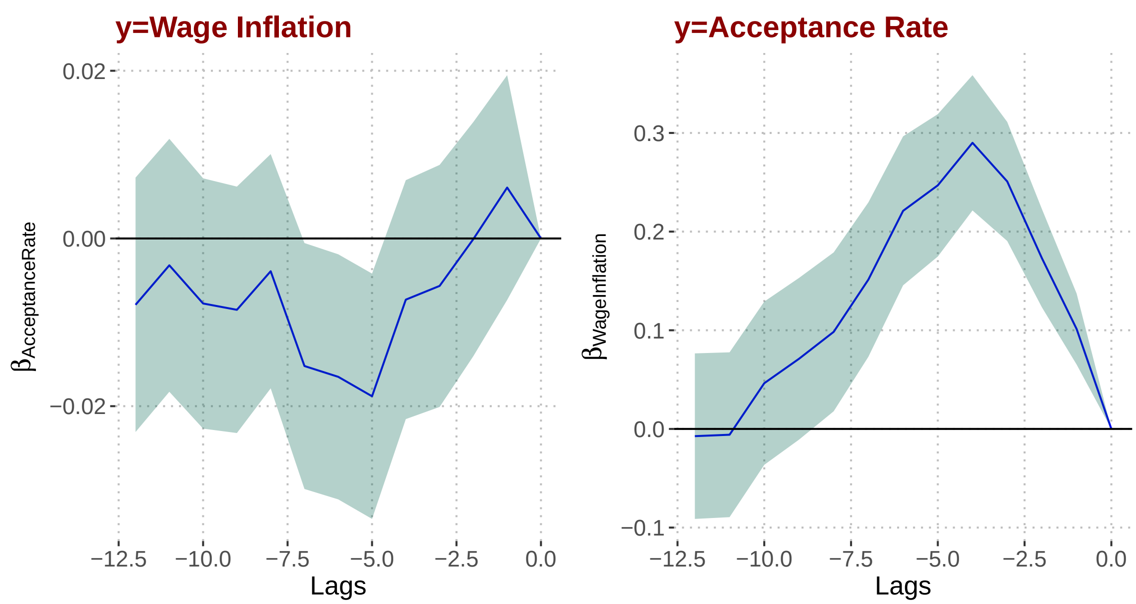


Figure 3: The left panel presents the coefficient estimates and the associated 95% CI for $\beta$ where wage inflation is regressed on the 'acceptance rate' with the specification in Equation 2. Each point corresponds to an estimate where the associated lag is in the x-axis. The right panel provides the same plot where the 'acceptance rate' is regressed on the wage inflation. See Appendix A for details of the data sources.

We use several popular monetary policy shock estimates in the literature. The first measure is computed from narrative records of FOMC meetings and internal forecasts of Federal Reserve by Romer and Romer (2004), which is updated until 2007 by Wieland and Yang (2016). The second measure is by Barakchian and Crowe (2013) that uses Fed Funds futures to see exogenous changes in policy. The third measure is by Sims and Zha (2006), who use structural VAR estimates to identify shocks to monetary policy. Fourth, fifth and sixth measures are by Gertler and Karadi (2015) and Nakamura and Steinsson (2018) who use high-frequency movements in financial series during FOMC announcements to identify monetary policy shocks[18]. The periods that match with the availability of job-to-job transitions data are all different across these measures, but results from regressions with all measures are consistent.

$$y_t = \beta x_{t-L} + \epsilon_t \tag{3}$$

Here, the majority of the coefficients are negative as expected. Furthermore, all but one of the significant coefficients are negative. These results further add to the evidence in support of our

[18] Readers should refer to Ramey (2016) for an excellent review on these and other monetary policy shock estimation methods.

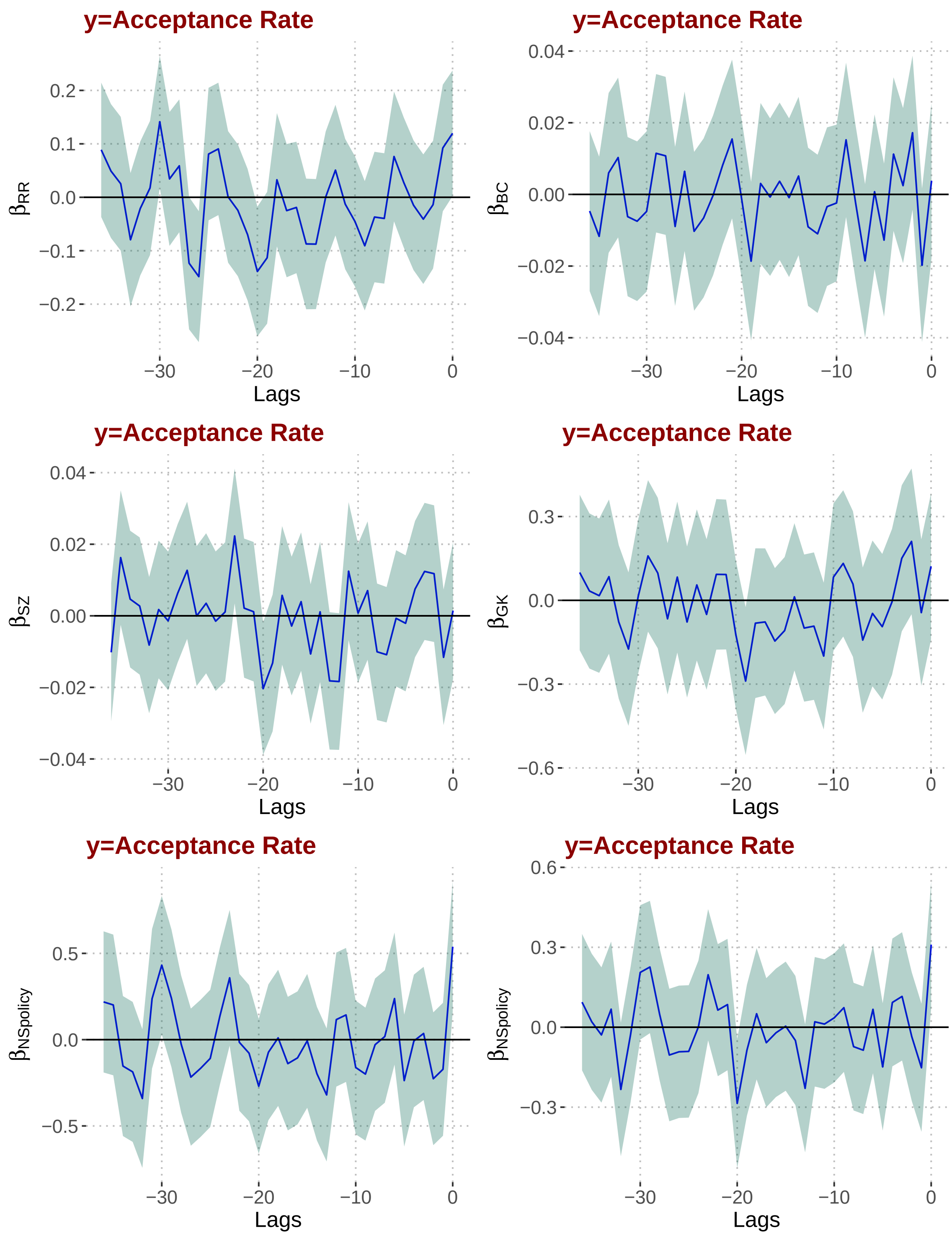


Figure 4: Each panel presents the coefficient estimates and the associated 95% CI for $\beta$ where 'acceptance rate' is regressed on a structural monetary policy shock estimate with the specification in Equation 3. Each point and the bar correspond to an estimate where the regressors are with the associated lag in the x-axis. See Appendix A for details of the data sources.

theory, that is, higher price inflation leads to higher job-to-job transitions.

## 2.3 Survey Evidence on Search Effort

The analysis here utilizes the Job Search supplement of the Federal Reserve Bank of New York Survey of Consumer Expectations (SCE)[19]. We use the publicly available data from 2013 to 2016. The Survey of Professional Forecasters (SPF), which is administered quarterly, provides one-year ahead inflation expectations[20].

To understand the effect of inflation on job search effort, the ideal measure would be the accumulated real wage loss (or gain) the agent has due to unexpected price movements. This object, unfortunately, is not available at the individual level. We instead use another object denoted as $\iota_i$:

$$iota_i = \prod_{t=\tau_{0i}}^{\tau_{si}} \frac{1 + i_t}{1 + \hat{i}_{\tau_{0i}}} \tag{4}$$

where $\tau_{0i}$ and $\tau_{si}$ denote the dates individual $i$ started her job and took the survey, respectively. $i_t$ denotes the realized CPI inflation rate and $\hat{i}_t$ denotes the SPF inflation expectations at date $t$. If the realized sequence of inflation rates is higher (lower) than the inflation expectations in the beginning, then the agent's real wage will be less (more) than intended, and $\iota_i$ will be larger. At the individual level, this measure only requires the job-start date of the worker, which is available in SCE.

The measure also has two main drawbacks. First, if the contract is renegotiated after the start date, the measure will break down. To alleviate this issue, we will focus on individuals who started their current job recently[21]. Second, SPF inflation expectations are only available at 1-year and 10-year horizons. Thus, we assume that inflation expectations $n$ year ahead are the same as the 1-year ahead inflation repeating itself $n$ times.

In the regressions below, we will restrict attention to full-time employees with a single job, who are (1) searching for another full-time job, (2) have been working for at least a year and (3)

[19]The SCE is administered monthly as a rotating panel, and the Job Search supplement adds detailed questions on job search behavior in the October survey. Since no respondent stays in the SCE for more than a year, the supplement becomes a repeated cross-section.

[20]Although the SCE provides the inflation expectations of each respondent, we believe the relevant inflation expectation that shapes a wage bargaining process is the one given by the firms and the policymakers.

[21]We will use workers with tenures for less than five years to have a compromise between guaranteeing that the start date is the last negotiation date and keeping a large sample.

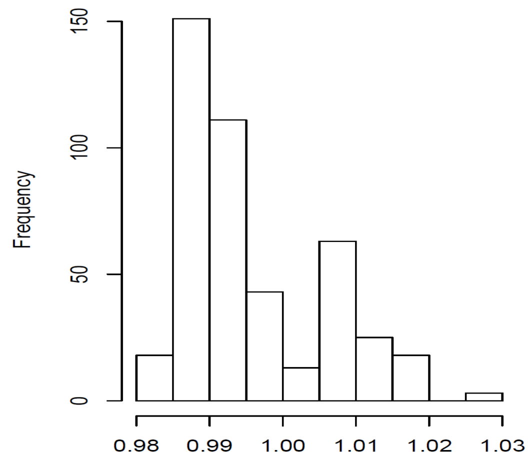

Figure 5: Histogram of $\iota_i$ Values

the reason for the search is not a firing notice or a non-work related reason.

The empirical design we will use is of the form:

$$y_i = \beta_0 + \beta_1 \iota_i + \beta_2 ln(tenure) + \gamma_{\tau_{0i}} + \alpha_{\tau_{si}} + \beta X_i + \epsilon_i \tag{5}$$

where $\gamma_{\tau_{0i}}$ and $\alpha\tau_{si}$ denote fixed effects for the job-start year and the survey year, respectively. $X$ includes demographic controls for age, gender, education, and marital status. $y_i$ denotes outcome variables measuring the extent of the search effort. In our exercise, we will use the number of offers received and a dummy variable for whether any offers were received in the past six months[22].

The identification idea is built on the random sampling of the surveys. Conditional on a job-start date, the survey dates of individuals are randomly assigned barring survival bias. Once we control for the job start and survey years and the tenure of the worker, we can treat $\iota_i$ as randomly assigned[23]. Figure 5 presents the histogram of $\iota_i$ values in the final sample.

Table 1 presents the results for an Ordinary Least Squares and a Linear Probability Model. The results indicate that unexpected inflation increases the likelihood of receiving an offer as well as the number of offers received at a 5% level. The 'Wage Mistake' variable is a ratio and is expected to be centered around 1. According to our estimates, a 1% positive inflation shock translates to

[22]SCE has other potential outcome variables such as the number of employers applied and the hours spent searching. However, any measure that quantifies effort through intermediate steps requires caution. The time spent searching or employers contacted are highly related to whether the specific type of effort translates into offers. For example, a high amount of time spent might indicate employee's inefficient search strategies. Similarly, a large number of employers contacted might indicate a quantity/quality trade-off in the application strategy.

[23]According to our identification argument, the demographic controls are also not strictly required. We include them only to reduce the regression variance. Including them has minimal effect on our quantitative results.

7.9% higher probability of receiving an offer and 0.17 more offers on average. Later in Section 4, we will use these coefficients to validate our model's ability to assess the relationship between inflation and job-to-job transitions correctly.

| | *Dependent variable:* | |
|---|---|---|
| | Number of Offers Received | Received (0-1) |
| | (1) | (2) |
| WageMistake | $17.395^{**}$ | $7.920^{**}$ |
| | (7.293) | (3.991) |
| Observations | 374 | 374 |
| $R^2$ | 0.189 | 0.082 |
| Adjusted $R^2$ | 0.155 | 0.043 |
| Residual Std. Error (df = 358) | 0.536 | 0.293 |
| F Statistic (df = 15; 358) | $5.555^{***}$ | $2.118^{***}$ |

$^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

Table 1: Each column presents the coefficient estimate for $\beta_1$ and the associated standard error with the specification in Equation 5. The independent variable is $\iota_i$ as constructed in Equation 4. The dependent variables are the number offers received and whether an offer was received by the respondent in the past six months respectively. The controls whose estimates are excluded from the table are job-start date, survey date, tenure, age, gender, education, and marital status. See Appendix A for details of the data sources.

# 3 The Model

## 3.1 Environment

The environment has two main frictions that are required to generate the monetary non-neutrality. First, firms and employees are not allowed to sign state-contingent contracts. Second, search frictions prevent perfect competition in the labor markets. Therefore, shocks to inflation introduce shifts in real wages of existing employees. Since employed also search on the job, the model exhibits monetary non-neutrality even though the wages of new hires are completely flexible. If all labor contracts were inflation-adjusted or labor markets were competitive, our model would exhibit monetary neutrality.

Here, we describe an environment where all variables are real. We then introduce shocks to the real wages of existing employees as inflation shocks and match these shocks to the discrepancy between the inflation forecasts and the realized inflation in the data. This will allows us to avoid nominal variables in our modeling which can be conceptualized as a limit of the classical New Keynesian model where pricing frictions go to zero[24].

#### 3.1.1 Preferences

The economy consists of a continuum of individuals with measure one and a continuum of firms with positive measure. Both the workers and the firms are risk-neutral and maximize the expected discounted income/profits. Time is discrete, and firms and workers share the same discount factor, $\beta \in (0, 1)$.

#### 3.1.2 Production Technology

There is a single homogeneous consumption good in the economy. When a worker and a firm match, they produce $y + z$ units of output. The first component, $y$, is the aggregate productivity, and it is the same across firms. The second component, $z$, is match specific. Upon meeting, $z$ is drawn from a distribution $\mathcal{G}$ and remains the same until separation.

Unemployed workers produce $b$ units of output.

#### 3.1.3 Meeting Technology

Workers and firms need to find each other to produce. Search is directed, and markets are indexed by the value offered by a firm to a worker. We denote submarkets by $X \in \mathbb{R}$.

Both unemployed and employed workers can search for a job. After they choose in which submarket to search for a job, workers choose the search effort, $e$. The cost of exerting effort is denoted by $c(e)$ and it is a strictly increasing and convex function with the following properties: $c(0) = 0, c'(0) = 0$[25].

Firms also choose in which submarket to post their vacancies. The cost of opening a vacancy for one period is $\kappa > 0$.

[24] We choose to avoid a full New Keynesian structure with pricing frictions. First, this allows us to isolate the effects of inflation through the labor market, without having to worry about other moving parts. Second, once included, pricing frictions require dynamically optimizing firms that break block-recursivity. Thus, we would be forced to use Taylor approximations to solve the model.

[25] We consider the search cost as a utility cost, thus it doesn't appear in the output calculations.

In a submarket, firms and workers meet each other via a constant returns to scale matching function, $M$. Given $v$ measure of vacancies and $E$ unit of total search effort, there are $M(v, E)$ measure of matches. Constant returns to scale assumption implies that market tightness $\theta$, i.e. vacancy-to-total search effort ratio, is sufficient to characterize the probability of matching. Specifically, a worker that exerts $e$ unit of search effort finds a job with probability $ep(\theta)$, where $p : \mathbb{R} \to [0, 1]$ is a strictly increasing and concave function with following properties: $p(0) = 0, p(x) \to 1$ as $x \to \infty$. On the other hand, a vacancy meets a worker with probability $q(\theta)$, where $q : \mathbb{R} \to [0, 1]$ is a strictly decreasing function with the following property: $\theta q(\theta) = p(\theta)$.

After a firm and a worker meets, they draw match productivity $z$ and decide whether to form a match or not.

### 3.1.4 Wage Setting

The contract space is limited to fixed-wage contracts. In other words, if a firm and a worker meet in a submarket $X$ and decide to form a match, then firm offers a wage rate $w$ that provides an expected lifetime utility of $X$ to worker, taking into consideration the search effort cost and the separation risk (either exogenous or through the worker finding a better job). $X$ and the aggregate state are sufficient to pin down the wage, since it depends on future lifetime utility $X$, not past outcomes. Also, the match productivity does not affect the lifetime value of the worker since it is constant throughout the firm-worker match. Let $\psi$ be the aggregate state of the economy, which consists of aggregate productivity $y$ and distribution of workers across jobs and wages $\Gamma(z, w)$[26]. We denote the entry wage of a worker in submarket $X$ when the aggregate state is $\psi$ by $h(X, \psi)$.

### 3.1.5 Timeline

Each period is divided into five sub-periods. In the first sub-period, aggregate productivity $y$ is drawn. In the second sub-period, exogenous separations occur with probability $\delta \in (0, 1)$. In the third sub-period, workers choose where to search and how much effort to exert. In this stage, workers who were separated from their job in the current period cannot search for a job; they remain unemployed with probability one. In the fourth sub-period, workers and firms meet and

[26]Unlike Menzio and Shi (2011), the wage distribution matters for determining future tightness because it determines the aggregate search effort.

decide whether to form a match. In the last sub-period, production takes place, and wages are paid.

### 3.1.6 Discussion of the Model Elements

While setting the environment, we make five main simplifications. Four of them are innocuous while the fifth is not.

First, we denote all the variables in real terms. Second, we avoid modeling an inflation process with rational expectations over it. Third, we assume fixed-wage contracts although all that is needed for the mechanism is that they are not state-contingent. In principle, we can focus on nominal wages, allow an inflation process that follows an AR($\infty$) and contracts that are functions of time. In that scenario, employees and firms could sign contracts that take the expected future inflation into account and designate an associated increase in nominal wages over time. Therefore, nominal wages would follow a path that leaves the real wages constant over time absent shocks to inflation and aggregate productivity. Using the real wages as the model element allows us to abstract from the expected paths of the nominal variables and focus on the shocks to the inflation process. None of these three simplifications have a bearing on the final results while they simplify the notation greatly.

Fourth, we don't allow firms to make counter offers for their poached employees. In theory, this might result in workers moving to jobs with lower productivity than their current jobs, which wouldn't happen if the incumbent firms could respond. We make the assumption for computational simplicity. More importantly, in our quantitative exercise, we don't observe this behavior with the calibrated parameters. Therefore, allowing the firms to respond should have no quantitative effect on our results.

The fourth simplification, namely, treating inflation as an exogenous process, is not completely innocuous. In a fully-fledged New Keynesian model, output shocks and monetary shocks both contribute to determining the inflation. Therefore, treating the inflation shocks as completely independent from output shocks would not be entirely correct. On the other hand, introducing firms that price dynamically would break the block-recursivity of the equilibrium. Thus, whenever we draw conclusions from the past data, we will not only rely on the inflation series. Instead, we will focus on the discrepancy between the inflation expectations and the realized inflation while remaining agnostic on how these expectations are formed in the economy.

## 3.2 Equilibrium

### 3.2.1 Problem of a Firm

Since the production technology is constant returns to scale, the size of the firm is indeterminate. Hence, we consider single vacancy firms. Let $K(w, z, \psi)$ be the value function of a filled vacancy with match productivity $z$, wage rate $w$ and aggregate state $\psi$. Observe that a firm is willing to form a match in submarket $X$ if and only if the match productivity $z$ satisfies $K(h(X, \psi), z, \psi) \geq 0$. Since the firm value is increasing in $z$, define $\underline{z}$ such that $K(h(X, \psi), \underline{z}, \psi) = 0$. If such $\underline{z}$ exists, the expected value of finding a worker is:

$$J(X, \psi) = \int_{z \geq \underline{z}} K(h(X, \psi), z, \psi) dG(z).$$

The free entry condition implies that

$$k \geq q(\theta) J(X, \psi), \tag{6}$$

where left-hand side is the cost of vacancy, and the right-hand side is the expected value of a vacancy, which is the product of the probability of finding a worker and the expected value of a filled vacancy. This condition holds with equality whenever there is a positive mass of workers searching for a job in submarket $X$. Hence, there is a one-to-one relationship between market tightness $\theta$ and $(X, \psi)$. Hence, we can write $\theta(X, \psi)$ as the market tightness in active submarkets.

Let $\bar{p}(H(w, \psi), \psi)$ be the probability that a worker leaves the job when his lifetime value is $H(w, \psi)$ and the aggregate state is $\psi$. Then,

$$K(w, z, \psi) = y + z - w + \beta(1 - \delta)\mathbb{E}\left[(1 - \bar{p}(H(w, \psi'), \psi')K(w, z, \psi)\right] \tag{7}$$

The model has endogenous separations, which affect the wage-setting problem in a non-trivial way. In a search model where job switches are efficient, a la Postel-Vinay and Robin (2002), the probability of losing a worker is completely exogenous. Thus, the sequential auctions protocol dictates firms to pay the minimum wage that will allow them to keep/attract the worker. Once search effort is introduced, firms may want to offer a wage that is more than absolutely needed to reduce the incentives of the worker to exert search effort and attract more offers. This kills the simple structure of the sequential auctions protocol. The additional complication is smaller in a directed search framework, however, results in a firm value function $K$ that is not monotone in the wage (or value) offered.

#### 3.2.2 Problem of an Unemployed Worker

Consider an unemployed worker. We write down the problem of the unemployed right before the production sub-period. The value function of an unemployed worker is

$$U(\psi) = b + \beta \mathbb{E}\left[\max_e eR(\psi', U) - c(e) + U(\psi')\right], \tag{8}$$

where $R(\psi, V)$ is return to searching in the optimal submarket for an agent with lifetime value of $V$:

$$R(\psi, V) = \max_x p(\theta(\psi, X))(X - V)(1 - G(\underline{z}(\psi, X)))$$

$e$ does not appear in $R(\psi, X)$, because search effort is exerted after the choice of submarket[27]. After the choice of submarket, worker chooses an effort level to maximize the term inside the brackets in (9).

#### 3.2.3 Problem of an Employed Worker

Similarly, we can define the value function of an employed worker as:

$$H(w, \psi) = w + \beta \mathbb{E}\left[\delta U(\psi') + (1 - \delta)\max_e (eR(\psi', H(w, \psi')) - c(e) + H(w, \psi'))\right]. \tag{9}$$

#### 3.2.4 Equilibrium Definition

Following Menzio and Shi (2011), we consider block recursive equilibria. In a block-recursive equilibrium, policy functions do not depend on the distribution of workers across jobs. Hence, the only relevant aggregate variable is aggregate productivity $y$, i.e., $\psi = y$[28].

[27]Since a worker is measure zero, his choice of $e$ does not effect $\theta$, hence it does not effect the choice of submarket.

[28]Since the search effort choice is an innocuous extension of the framework in **?**, we do not prove existence and uniqueness of the block-recursive equilibrium here. Schaal (2017) provides a discussion of the possible scenarios where

A block-recursive equilibrium consists of a market tightness function $\theta : Y \times \mathbb{R} \to \mathbb{R}_+$, a value function for the unemployed $U : Y \to \mathbb{R}$, a value function for the employed $H : \mathbb{R}_+ \times Y \to \mathbb{R}$, a value function for the firm $K : \mathbb{R}_+ \times Z \times Y \to \mathbb{R}$, optimal choice of submarket $m : \mathbb{R} \times Y \to \mathbb{R}$, optimal choice of search effort $e : \mathbb{R} \times Y$, entry wage $h : \mathbb{R} \times Y \to \mathbb{R}$ and the cutoff for match productivity $\underline{z} : \mathbb{R} \times Y$ such that:

1. $\underline{z}(X, \psi)$ satisfies $K(h(X, \psi), \underline{z}, \psi) = 0$,
2. entry wage $h(X, \psi)$ solves $H(h, \psi) = X$,
3. $H(w, \psi)$ satisfies (9), $U(\psi)$ satisfies (8), $K(w, z, \psi)$ satisfies (7) where probability that a worker finds a job is $\bar{p}(w, \psi) = e(m(H(w, \psi), \psi))p(\theta(\psi, m(H(w, \psi), \psi)))(1 - G(\underline{z}))$,
4. $e(V, \psi)$ and $m(V, \psi)$ solve worker's problem,
5. $\theta(\psi, X)$ satisfies the free entry condition (6).

### 3.3 Effect of a Decrease in Real Wage

What happens if a worker's real wage decreases for some exogenous reason, for example, inflation? In this section, we show that there are two competing mechanisms: a decrease in selectivity in on-the-job search and an increase in the search effort. First, we prove that when a worker's current lifetime utility decreases, she searches in a lower-valued submarket, which has a lower cutoff for match-specific productivity. Second, we prove that the worker increases the search effort.

**Lemma 1.** $\underline{z}(X, \psi)$ *is increasing in promised lifetime utility* $X$.

This lemma states that as the promised lifetime utility increases, to form a match, a better match specific productivity draw is needed. The intuition is clear: if a firm promises higher value, its lifetime value decreases. Hence, at the marginal match specific productivity, the firm starts making a loss. Therefore, the firm is more selective in high indexed markets.

**Lemma 2.** $m(V, \psi)$ *is increasing in current lifetime utility* $V$.

This lemma states that workers with low current lifetime utility searches in a market that promises lower lifetime utility compared to a worker with higher current lifetime utility. This

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block-recursivity may fail.

mechanism implies a job ladder, workers start from the bottom and gets better lifetime utilities as they find new jobs and climb the job ladder.

**Lemma 3.** *$R(\psi, V)$ is decreasing in current lifetime utility $V$.*

As a worker's current lifetime utility increases, there is a lower gain from finding a better job. Hence, return to searching for a job increases. This mechanism also implies that search effort is decreasing with lifetime value.

**Lemma 4.** *$e(V, \psi)$ is decreasing in current lifetime utility $V$.*

Lemmas 1 and 2 show that a worker with a lower current lifetime utility search in a lower indexed submarket, in which cutoff for the match-specific productivity is lower. Hence, if a worker's wage decreases, the expected productivity of her next job is lower than the expected productivity in the market she previously searched in[29]. On the other hand, Lemma 4 shows that the worker increases his search effort. Hence, the probability of moving to a better job increases.

At the micro-level, inflation has a direct impact on individual's lifetime utility. However, at the macro level, inflation does not have a direct effect, i.e., if workers do not change their behavior, there would be no change in the aggregate output. However, due to these two competing channels, the aggregate output might decrease or increase in the short-run due to inflation. One time inflation shock does not have an impact on the steady-state, thus, there are no long-run implications.

If the first channel dominates, workers end up with lower match specific productivities, which leads to lower aggregate output. If the second channel dominates, workers increase their search effort and form new matches with higher match productivity. This mechanism leads to a higher aggregate output. Therefore, impact of an inflation shock is ambiguous. We proceed to quantify the importance of each channel in Section 4.

# 4 Quantitative Analysis

This section presents the preliminary calibration strategy and the quantitative results.

[29]There might even be a probability that she ends up at a worse job than the current one she has. In the calibrated model, we don't observe this possibility.

### 4.1 Calibration Strategy

For the output predictions to have a quantitative interpretation, two implied elasticities should be plausible: (1) the response of job-to-job transitions to an inflationary shock and (2) the response of aggregate output to job-to-job transitions. We measure the former elasticity from micro-data that documents how workers adjust their search behavior with inflationary shocks (see Section **??**). The latter can be inferred from wage increases following job switches and a measure of how surplus is shared between firms and workers. Although matching these two elasticities is necessary for pinning down the output response, it is not sufficient. The response of the aggregate output to job-to-job transitions depends on the underlying reasons for these transitions. The output response following increased transitions due to a labor demand shock does not necessarily equal the response due to an inflationary shock. Thus, it is crucial to model these two together instead of stitching two elasticities that are computed separately.

We use a telephone-line matching function: $p(\theta) = \theta\left(1+\theta^{\gamma}\right)^{-1/\gamma}$[30] and assume the match specific productivity distribution $\mathcal{G}$ follows a Pareto distribution with location parameter $z_{min}$ and shape parameter $z_{shape}$. Lastly, we assume a quadratic search cost function $c(e) = Ae^2$ where the level potentially differs for the employed $A_e$ and the unemployed $A_u$.

The full set of parameters necessary to compute the model is the vector:

$$\Omega = \{\beta, \delta, \gamma, \kappa, A_e, A_u, b, z_min, z_shape, \rho_y, \sigma_y\} \tag{10}$$

The model period is taken to be a month. We normalize $z_min$ to equal the unemployment benefit replacement rate, calibrate $\beta$ and $\delta$ externally, and calibrate the remaining parameters internally. We calibrate the parameters to match the steady state moments, except for the parameters that determine the process of aggregate productivity process. Then, we calibrate the aggregate productivity process to match the business cycle statistics.

We set the monthly discount factor $\beta = 0.95^{1/12}$ and exogenous separation rate $\delta = 0.011$ consistent with the average EU rate in 2005 (Fallick and Fleischman (2004)).

[30] The telephone-line matching function, proposed by Stevens (2007), is a flexible matching function that has the Cobb-Douglas as a special case.

| Parameter | Value | Moment | Data | Model | Source |
|---|---|---|---|---|---|
| $\gamma$ Match. Funct. Elasticity | 3 | UE | 0.30 | 0.30 | Shimer '05 |
| $A_e$ for employed | 0.066 | EE | 0.024 | 0.016 | Shimer '05 |
| $A_u$ for unemployed | 4.5 | labor share | 0.60 | 0.60 | |
| b Unemployment Flow | 5.50 | residual log wage q75 | 0.54 | 0.32 | CPS |
| $z_{shape}$ | 1.95 | residual log wage q25 | -0.32 | -0.2679 | CPS |
| $\kappa$ Vacancy Cost | 0.066 | median tenure | 48 | 31 | CPS |

Table 2: Calibrated parameters All parameters in the table are jointly calibrated to match all the moments. The last column provides an intuitive mapping between the parameters and the moments that are most related. Avg. labor prod. is constructed by HP filtering the logged series with smoothing parameter $10^5$. In order to construct the residual wage distribution, we first construct an hourly wage measure through dividing the weekly wage by the usual hours worked. Then, we regress the hourly wage on age, age squared, gender, race, marital status, and education level in the cross-section for each month of 2005 in CPS. Lastly, we take the average of the quantiles of the distributions of residuals from each regression.

#### Calibration Idea

The model doesn't admit an analytic expression for the steady state distribution of workers across jobs, hence we stick to discussing the broad intuition of how the moments inform the parameter values. The calibration uses all moments to discipline all parameters, since general equilibrium effects through market tightness prevents isolating the response of different moments.

The residual wage distribution informs the match productivity distribution $z_s hape$, and the flow benefit of unemployment $b$. The flow benefit disciplines the left tail because the wage bargaining between the firm and an unemployed worker depends on the outside option of the worker. The right tail depends on how large the match productivity can be, hence on $z_s hape$.

The employment-to-employment (EE) and unemployment-to-employment (UE) transition rates inform the search effort cost level parameters for the employed $A_e$ and the unemployed $A_u$ respectively. A higher transition rate implies a lower cost.

The labor share disciplines the vacancy cost $\kappa$, hence the surplus sharing between the firm and the worker in the model. A higher labor share implies a low $\kappa$. Lastly, the median tenure helps discipline the matching function elasticity $\gamma$. As the elasticity gets larger, firms become more aggressive with the wage postings and the median tenure goes down.

#### Calibration Results

The calibrated parameters together with the matched moments are given in Table 2.

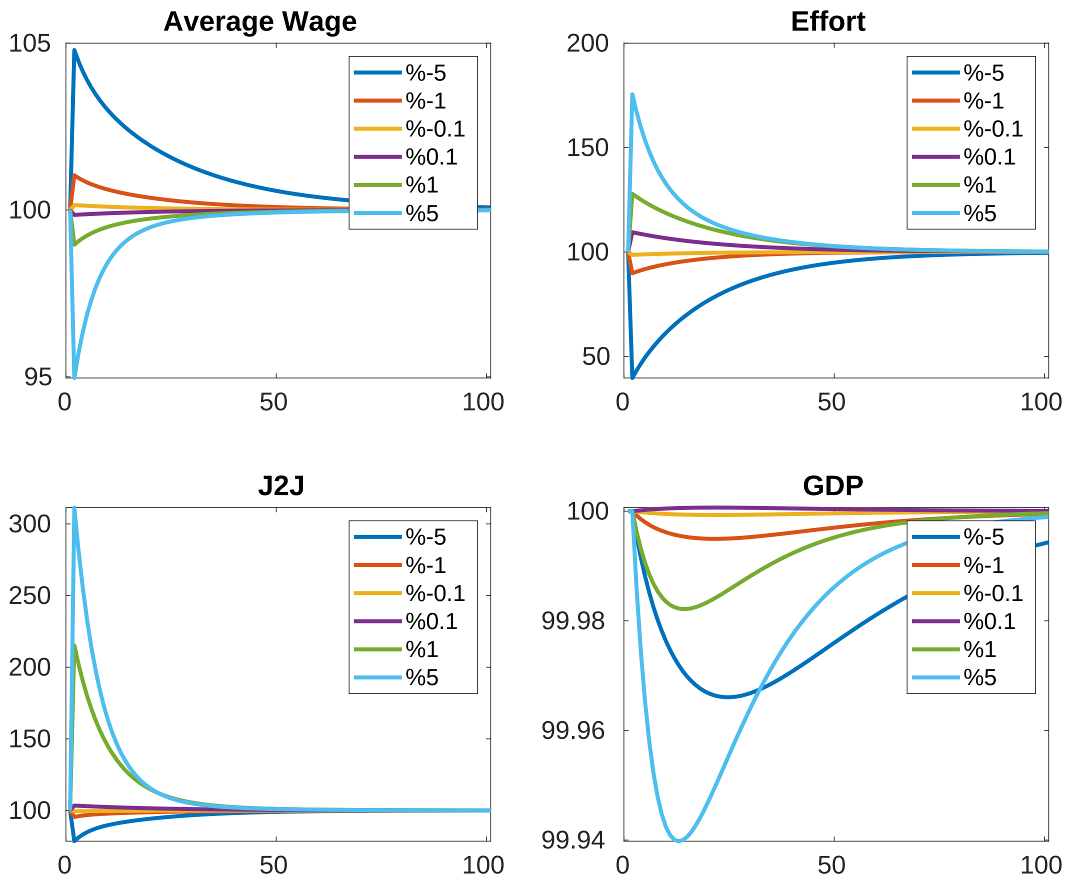


Figure 6: Each panel presents the impulse response functions with respect to an unexpected inflation shock of different sizes.

### 4.2 Unexpected Inflation Shock

This section presents how the economy responds to unexpected shocks to inflation of different sizes. In particular, the quantitative findings confirm the analytic results in Section 3.3. While small positive inflation shocks increase the output in the short run, large positive inflation shocks decrease it. Negative shocks to inflation uniformly decrease the output.

Figure **??** displays the impulse-responses for shocks to inflation of sizes 1 pp and 0.5 pp. The instantaneous change in average wages reflects the size of the inflation shock. The job-to-job transition rate increases following both shocks together with the average on-the-job search effort. However, while the smaller shock brings a short-run boost to output, the larger shock causes a short-run decline. Here, one important implication of the counter-acting mechanisms manifests itself. The drop in real wages brings the search effort up, which results in an increase in output. On the other hand, the same drop causes the employed to be more nervous about finding a new job more quickly. Hence, they look for jobs in markets where it is easier to find a job, where wages and productivity are lower as well. When the shock is small enough, the increased number of switches dominates the fact that each switch is less productivity-enhancing. When the shock gets larger, the latter channel starts to dominate and we see a drop in output.

Since the wages of new hires are perfectly flexible, job switches undo the effects of the one-time inflation shocks. Therefore, the model exhibits money neutrality in the long run.

## 5 Conclusion

In this paper, we try to understand the positive correlation with inflation and job-to-job transitions in the economy. We first show reduced form and causal evidence suggesting higher inflation causes more job-to-job transitions. In time-series and panel structures, we find that shocks to inflation precede shocks to job-to-job transition rates: lags of inflation are consistently good predictors of job-to-job transitions. In addition, using several monetary policy shock estimates, we argue the relationship seems to be causal and economically significant: 1% increase in the nominal interest rate corresponds up to 6.5% decrease in job-to-job transition rates in the U.S. We proceed by constructing a model that can explain these observations. In settings with wage rigidities, higher than expected inflation rates increase the benefit of searching on the job. As employees increase their search effort, more job-to-job transitions occur and allocation of labor across firms improves in the short run. The mechanism carries important implications for monetary policy: an expansionary monetary policy can improve the allocation of resources in the economy and increase productivity in the short run.

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# Appendices

## A Data Sources

#### A.0.1 Monthly Data

For the job-to-job flows, we use the series made available by Fujita et al. (2019)[31] that is computed from the Current Population Survey (CPS). The unemployment-to-employment transition (UE) rates are from Fallick and Fleischman (2004), similarly computed from the CPS[32]. The Consumer Price Index (CPI) inflation and the unemployment rate (U) series are from the U.S. Bureau of Labor Statistics[33]. The wage inflation series is computed the same way using the 'Average hourly earnings of production and nonsupervisory employees, total private, not seasonally adjusted', from the Current Employment Series (CES)[34].

#### A.0.2 Yearly Data

CPS provides an approximate measure for yearly job-to-job transition rates starting at 1976. We use the methodology proposed by Mukoyama (2014) to deal with the time aggregation bias introduced by low frequency of data[35].

#### A.0.3 Quarterly Data

For the job-to-job flows, we use the series J2JHireR and J2JSepR which are computed by dividing the number of hires (or separations) with no unemployment period in between to the total labor

[31] This series is based on the method introduced by Fallick and Fleischman (2004) while corrects for an attrition bias that starts with the changes in the survey questions in 2007 (https://sites.google.com/site/fabienpostelvinay/working-papers/EEProbability.xlsx?attredirects=0&d=1). We repeat our empirical exercises using the original series by Fallick and Fleischman (2004) as a robustness check. The results are BLANK and are presented in Appendix BLANK.

[32] https://www.federalreserve.gov/pubs/feds/2004/200434/200434abs.html.

[33] The analyses where CPI is replaced with Personal Consumption Expenditures (PCE, https://fred.stlouisfed.org/series/PCEPI#0) provide quantitatively and qualitatively similar results.

[34] https://beta.bls.gov/dataViewer/view/timeseries/CEU0500000008

[35] The monthly series is based on the question introduced to CPS at 1994, that asks whether there were any changes in the employment status of the worker since last month ("SAMEMP"). The yearly data asks whether the employee works for the same employer as last year. If the answer is no and there hasn't been a long unemployment spell, there needs to be at least one switch. However, there is no way to confirm multiple switches within a year. Furthermore, recall becomes a bigger problem when the time period the respondent is expected to remember is further back. Although the data quality is potentially lower due to these issues, the yearly series goes back to high inflation periods in the U.S., thus provides important variation in inflation levels that is not present in recent years.

force. The two series closely follow each other and give very similar qualitative and quantitative results. In the main text, we focus on the analysis with J2JSepR. LEHD does not have information on unemployed-to-employed transition rates, therefore we use the variable NEHireR instead. This variable is computed by dividing the number of hires (or separations) from non-employment to the total labor force. We get state-level wage inflation data from the Quarterly Census of Employment and Wages (QCEW). Specifically, we use the percentage change in state-level average weekly wages between quarters t and t-4 in privately owned firms[36]. We use Local Area Unemployment Statistics (LAUS) from the BLS for state-level unemployment and labor-force data[37].

## B Evidence on the Extent of Wage Indexation

Explicit measures of what fraction of wage contracts are indexed to inflation are unavailable for the U.S. economy. The measures that are based on the actual contract terms are restricted to collective agreements in the U.S., which varies in coverage over the years and does not apply to a random sample of the workers. Measures based on changes in the nominal wages are imperfect due to several other factors affecting the wage process. However, even the most conservative estimates imply a very low level of wage indexation (less than 25%) in developed countries. Here, we discuss the implications of prior research on the extent of wage indexation.

#### B.0.1 Evidence Based on Contract Terms

The main papers on the prevalence of 'cost-of-living adjustment' (COLA) terms in contracts are Card (1990) for Canada and Ragan Jr and Bratsberg (2000) for the U.S. Card (1990) looks at the universe of manufacturing union contracts (with more than 500 employees) signed between 1968 and 1983. He finds that 26% of them have an 'escalation clause' on average while the explicit indexation is very rare. The fraction with 'escalation clause' peaks at 65% in a period where the inflation is over 10%. Ragan Jr and Bratsberg (2000) use the U.S. Bureau of Labor Statistics data on collective bargaining settlements to see the prevalence of COLA provisions. They document that even though 61% of the settlements had COLA provisions back in 1976, it has fallen all the way

[36] We exclude the public sector to isolate the market forces in the wage changes. Using data from all the firms has little impact on qualitative and quantitative outcomes.

[37] See https://www.j2jexplorer.ces.census.gov, https://www.bls.gov/cew/downloadable-data-files.htm, and https://www.bls.gov/lau/.

to 22% in 1996 when the data is no longer available. The COLA provisions are known to be much less prevalent among non-union workers. With the decline in unionization, collective agreements cover a smaller fraction of the labor force in either country today. We consider these measures as an upper bound on the extent of wage indexation. Druant et al. (2012) utilize a firm-level survey conducted in 17 European countries regarding wage adjustment practices. Across 15,000 firms from all industries, they document that only 11.5 % of the firms employ any formal indexation clause in employment contracts while only 10.9% have any informal inflation considerations in wage setting[38]. More importantly, the survey also asks about the frequency of wage adjustments. This gives us a back-of-the-envelope mapping between the degree of indexation and the frequency of wage adjustments. Wage adjustments happen either yearly or more frequently for 74.4% of the firms. Thus, even when firms adjust wages frequently, this does not imply an implicit wage indexation.

#### B.0.2 Evidence Based on Wage Movements

McLaughlin (1994), using PSID data, finds that the effect of unanticipated inflation on nominal wage growth is consistent with 42% indexation between 1970 and 1986. Hofmann et al. (2012), using a DSGE model, infers the extent of wage indexation in the economy from the time variation in U.S. wage dynamics. They estimate the degree of wage indexation to be $0.17$ in 2000, compared to $0.91$ in 1974, which is roughly in line with the time path of COLA coverage in collective bargaining agreements[39]. More recently, Grigsby et al. (2019), using data from a payroll processing company in the U.S., found that approximately 36% of job stayers experience no nominal wage changes in a one-year period. Once contrasted with the evidence in Druant et al. (2012), the implied wage indexation should be less than 11.5%.

## C Proofs

**Lemma 1.** *$\underline{z}(X, \psi)$ is increasing in promised lifetime utility $X$.*

[38] There is still large variation across countries. In Belgium, 98.2% of the firms have automatic wage indexation while in Italy, only 5.8% of the firms have any form of wage indexation.

[39] A major implication from the paper is that wage indexation is a response to increasing monetary policy uncertainty. Thus, the level of indexation should be endogenous to run counter-factual exercises that change monetary policy. Since we focus on one-time shocks, we abstract from endogenous indexation.

*Proof.* Recall that $\underline{z}$ solves

$$K(h(X,\psi),\underline{z},\psi)=0.$$

Clearly, as promised lifetime utility $X$ increases, value of the firm decreases. In order to satisfy equality, $\underline{z}$ must be increased.

□

**Lemma 2.** *$m(V,\psi)$ is increasing in current lifetime utility $V$.*

*Proof.* Let$V_h > V_\ell$. We want to show that $m(V_h,\psi) \geq m(V_\ell,\psi)$. For simplicity, we drop the aggregate state variable, since we are only considering the change in current lifetime utility $V$ and denote the associated choices as $m_h$ and $m_\ell$ and associated market tightness as $\theta_h$ and $\theta_\ell$. Suppose the contrary: $m_h < m_\ell$. This implies that $m_\ell - V_h > m_h - V_h$. Since $m_h$ is the optimal choice for $V_h$

$$\begin{aligned}&p(\theta_h)(m_h - V_h) \geq p(\theta_\ell)(m_\ell - V_h)\\ \implies\ &p(\theta_h) > p(\theta_\ell).\end{aligned}$$

Rearranging the first line also gives us:

$$p(\theta_h)m_h - p(\theta_\ell)m_\ell \geq [p(\theta_h) - p(\theta_\ell)]V_h.$$

Similarly, since $m_\ell$ is the optimal choice for $V_\ell$

$$\begin{aligned}&p(\theta_\ell)(m_\ell - V_\ell) \geq p(\theta_h)(m_h - V_\ell)\\ &[p(\theta_h) - p(\theta_\ell)]V_\ell \geq p(\theta_h)m_h - p(\theta_\ell)m_\ell.\end{aligned}$$

Using combining these two conditions:

$$[p(\theta_h) - p(\theta_\ell)]V_\ell \geq [p(\theta_h) - p(\theta_\ell)]V_h \implies V_\ell \geq V_h.$$

Which contradicts the assumption that $V_h > V_\ell$. □

**Lemma 3.** *$R(\psi,V)$ is decreasing in current lifetime utility $V$.*

*Proof.* By envelope theorem:

$$R_V(\psi, V) = -p(\theta(m(V, \psi))) < 0.$$

Hence, $R$ is decreasing in $V$. □

# D Solution Method

We use Value Function Iteration with 20 grid points for the distribution of $z$, 5 points for the distribution of $y$, 200 points for the grid for $V$, and 600 points for the grid for $w$. We define $\tilde{K}(V, y, z) = K(h(V, y), y, z)$ for convenience and start with an initial guess $\tilde{K}^0(V, y, z)$. The algorithm works sequentially. At step $i$, we compute

1. $J^i(V, y)$ given $\tilde{K}^{i-1}(V, y, z)$
2. $\underline{z}^i(V, y)$ and $\theta^i(V, y)$ given $J^i(V, y)$
3. $U^i(y)$, $e^i(V, y)$, $R^i(V, y)$, and $m^i(V, y)$ given $\underline{z}^i(V, y)$ and $\theta^i(V, y)$
4. $H^i(w, y)$ given $e^i(V, y)$, $R^i(V, y)$, $m^i(V, y)$, $\underline{z}^i(V, y)$, $\theta^i(V, y)$, and $U^i(y)$
5. $K^i(w, y, z)$ given $e^i(V, y)$, $m^i(V, y)$, $\underline{z}^i(V, y)$, and $\theta^i(V, y)$
6. $h^i(V, y)$ given $H^i(w, y)$
7. $\tilde{K}^i(V, y, z)$ given $K^i(w, y, z)$ and $h^i(V, y)$

We stop when $d_{max}(\tilde{K}^i(V, y, z), \tilde{K}^{i-1}(V, y, z)) < \epsilon$ where $d_{max}$ gives the maximum distance between the two vectors.

# E A Model of Search Effort under Random Search

In this section, we present a random-search version of our model in Section 3. The random-search version here doesn't have the selectivity channel, since workers do not direct their search to particular types of firms.

### E.1 Preferences

The discrete-time economy is populated by a continuum of infinitely-lived workers and firms. The total measures of workers and firms are fixed and normalized to one. Each worker has ability $x$, which is distributed with cumulative distribution function $G$, and each firm has productivity $y$, which is distributed by cumulative distribution function $\Gamma$. Time is discrete.

Both firms and workers are risk neutral and have the same discount factor, $\beta \in (0, 1)$.

### E.2 Production Technology

There is only one consumption good in the economy. A worker-firm pair $(x, y)$ can produce $f(x, y)$ output, where $f$ is strictly increasing in both arguments and super-modular, i.e. $f_i(x, y) > 0$ for $i \in \{x, y\}$ and $f_{xy}(x, y) > 0$, where $f_i$ is the derivative with respect to $i$.

Super-modularity of $f$ implies that output maximizing allocation is to match high productivity workers with high productivity firms.

Each unemployed worker produces $b(x)$ unit of output by herself. Lastly, each worker-firm pair dissolves with probability $\delta$ in a given period.

### E.3 Meeting Technology

In order to produce workers and firms need to find each other through random search.

Both unemployed and employed worker can search for a job. In order to find a vacancy, workers need to exert search effort. $c(e)$ denotes the utility cost of exerting $e$ units of effort for the employed. For simplicity, we assume that search effort of unemployed worker is fixed to $1$ and there is no cost attached to this effort. However, employed person chooses $e$ optimally[40]. We assume $c(e)$ is convex and strictly increasing in $e$, with $\lim_{e \to 1} c(e) \to \infty$ to simplify matching probabilities.

Firms, on the other hand, choose how many vacancies to open. In order to open $v$ units of vacancies, a firm needs to pay $\kappa(v)$, where $\kappa(v)$ is convex and strictly increasing.

Let $E$ and $V$ be the total measure of search effort and vacancies, respectively. Total measure of matches to be formed is denoted with $M(E, V)$, for a given $E$ and $V$. We assume that $M(E, V)$ is homogeneous of degree one. Then, measure of matches per unit of search effort is given by

[40] It is assumed that production level does not depend on search behavior of the worker.

$M(1, E/V)$. Let $\lambda$ denote the probability that one unit of search effort matches a vacancy: $\lambda = M(E, V)/E$. The probability that a vacancy meets with a worker is given by $\lambda^f = M(E, V)/V$.

We define market tightness to be the measure of vacancies available per unit search effort and denote it with $\theta = V/E$. Homogeneity of degree one implies that match probabilities of workers and vacancies only depend on aggregate quantities through tightness: $\lambda(\theta) = M(\theta, 1)$, $\lambda^f(\theta) = M(1, 1/\theta)$. This implies that $\lambda^f(\theta) = \theta\lambda(\theta)$.

### E.4 Wage Setting

Upon meeting, firm makes a take or leave it offer to worker. Firms can only propose constant nominal wage contracts to workers from which workers can walk away from anytime. Contracts can be re-negotiated without cost.

Contract space is not complete. Firms cannot make wage rate contingent on the state of the economy. Moreover, search effort of worker is not contractible. Hence, when a firm makes an offer, it needs to take into account the search effort of the worker.

When an employed worker meets with another vacancy, incumbent firm can make a counter-offer. As in **?**, this triggers Bertrand competition between incumbent firm and poaching firm.

Let $V_t(w, x, y)$ be the lifetime utility of a worker type $x$ who is employed at firm $y$ with a wage $w$ and let $J_t(w, x, y)$ be the present discounted profits of a firm with productivity $y$ that employs worker $x$ at wage $w$[41]. Consider two firms with productivity $y' > y$ that are bargaining over a worker with type $x$. In Bertrand competition, the maximum that a firm can offer as wage is the entire output. In such a situation, the lifetime utility of a worker type $x$ would be $V_t(f(x, y), x, y)$ with firm $y$. Therefore, firm $y'$ should solve the following problem:

$$\max_{w} J_t(w, x, y')$$
$$s.t.\ V_t(w, x, y') \geq V_t(f(x, y), x, y).$$

where constraint ensures that firm $y$ cannot outbid the offer.

When a firm makes an offer, it needs to take into account the search effort of the worker. Even though an increase in $w$ decreases the output share of firm, it discourages the worker from

[41]For brevity, instead of writing aggregate states in the value function, we index value functions with the time subscript.

searching for a job and getting new offers, which is good for the firm. Depending on which effect dominates, value function $J_t$ might be increasing or decreasing with $w$. To simplify the model, as in Postel-Vinay and Robin (2004), we assume that $J_t(w, x, y)$ is a decreasing function of $w$.

**Assumption 1.** *$J_t(w, x, y)$ is a decreasing function of $w$.*

This assumption implies that constraint must hold with equality, since $V_t(w, x, y)$ is increasing in $w$.

There are three possibilities for a worker employed at a firm with productivity $y$. First, she might match with a firm that has higher productivity, $y' > y$. In this case high productive firm wins the bargaining and worker changes his job. The worker's lifetime utility becomes $V(f(x, y), x, y)$[42]. Let $\phi(x, y, y')$ be the wage that solves $V(\phi(x, y, y'), x, y') = V(f(x, y), x, y)$. In other words, $\pi(x, y, y')$ is the wage rate of worker type $x$ when she moves from $y$ to $y'$.

In the second case, the worker matches with a firm that has lower productivity, $y > y''$, however poaching firm can offer higher lifetime utility to worker than she currently has. In this case, poacher cannot win the bargaining, though bargaining increases the wage of the worker in the current firm. In this case, the worker's lifetime utility increases to $V(f(x, y''), x, y'')$ and her wage increases to $\pi(x, y'', y)$.

The second case can only happen if the current lifetime utility of the worker is lower than the maximum utility she could get from the poaching firm, i.e. $V(w, x, y) < V(f(x, y''), x, y'')$. In this situation, there is a room for firm $y''$ to make an offer.

In the third case, the poaching firm's productivity is so low that it cannot make any offer that triggers Bertrand competition. In this case there is no change in the worker's wage and lifetime utility.

Let $\tilde{y}(w, x, y)$ be the minimum productivity level that a firm can trigger a bargaining. The following table summarizes the bargaining outcome between incumbent firm with productivity $y$ and poaching firm with productivity $y'$:

- $y' > y$: Poaching firm offers $\phi(x, y, y')$, worker moves to firm $y'$ and her lifetime utility becomes $V(f(x, y), x, y)$. See Figure ??.

[42]Here, since all comparisons happen at the same aggregate state, we suppress the time subscripts to reduce notation.

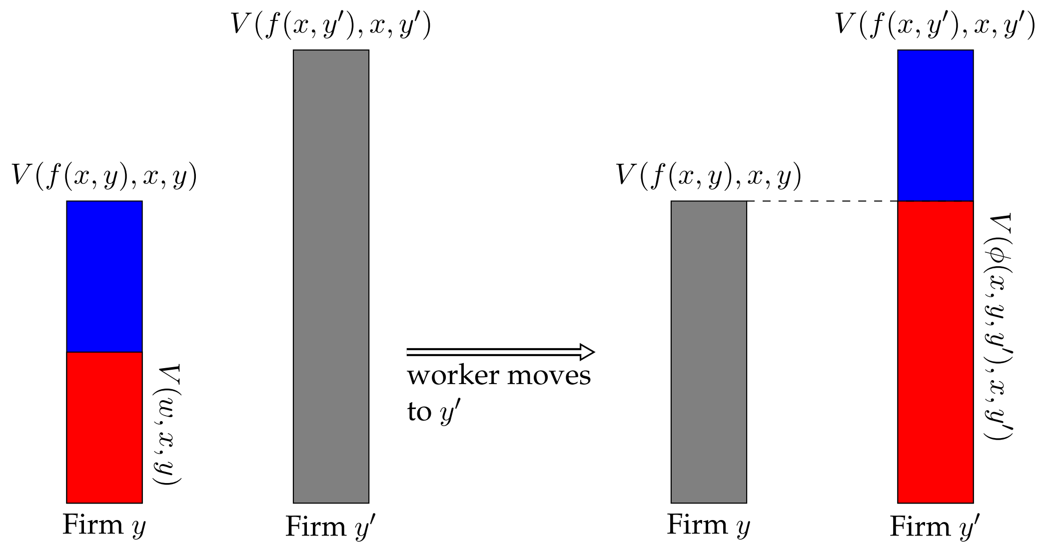


Figure 7: Worker $x$ in firm $y$ matches with firm $y' > y$.

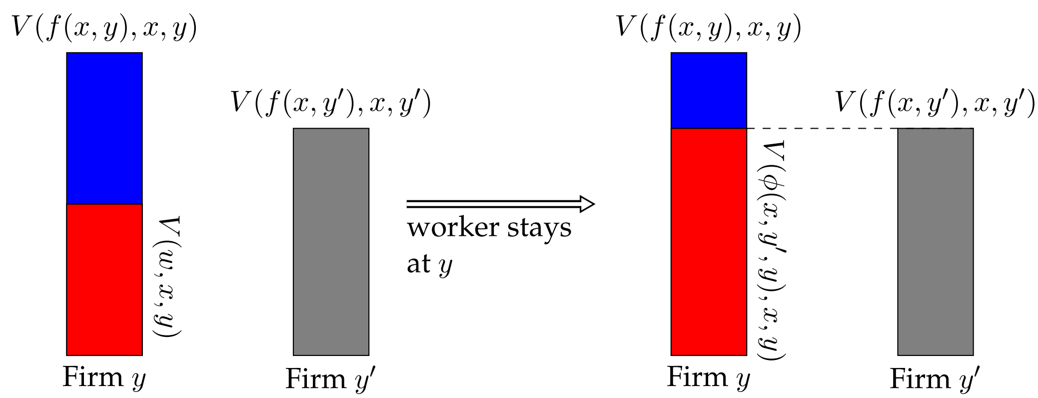


Figure 8: Worker $x$ in firm $y$ matches with firm $y' \in [\tilde{y}, y]$.

- $\tilde{y}(w,x,y) \leq y' \leq y$: Incumbent firm offers $\pi(x,y',y)$, worker stays with the incumbent firm and her lifetime utility becomes $V(f(x,y'),x,y')$. See Figure **??**.
- $y' < \tilde{y}(w,x,y)$: The worker ignores the poaching firm, stays with the incumbent firm and her lifetime utility remains $V(w,x,y)$. See Figure **??**.

Now consider an unemployed worker. If she meets a vacancy, the firm has the all the bargaining power, since there is no other firm to make a counter offer. Hence, the firm offers the wage rate that makes the unemployed worker indifferent. Let $\phi_t(x,0,y')$ be the wage rate that firm $y'$ offers to unemployed worker. $\phi_t(x,0,y')$ solves $V_t(\phi_t(x,0,y'),x,y') = U_t(x)$.

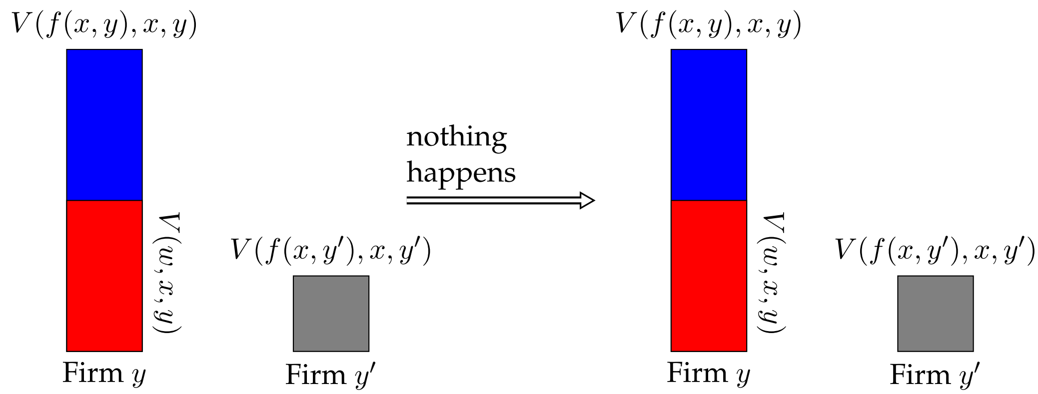


Figure 9: Worker $x$ in firm $y$ matches with firm $y' < \tilde{y}$.

### E.5 Market Tightness

Let $h(w,x,y)$ be the measure of workers with skill $x$ employed at firm $y$ earning wage $w$ and let $e^{\star}(w,x,y)$ be the optimal search effort. Let $u(x)$ be the measure of unemployed workers with skill $x$. Lastly, let $v(y)$ be the measure of vacancies posted by firms of type $y$.

Total search effort in the economy is given by

$$E_t = \int u_t(x)dx + \int\int\int e^{\star}_t(w,x,y)h_t(w,x,y)dwdydx.$$

Total measure of vacancies in the economy is given by

$$V_t = \int v^{\star}_t(y)dG(y).$$

Then, market tightness is given by

$$\theta_t = V_t/E_t. \tag{11}$$

We define the distribution of vacancies as $\Gamma$:

$$\Gamma_t(y) \equiv \int^y \frac{v_t(y')}{V_t}dy'.$$

with $\gamma_t(y)$ is the associated density function.

## E.6 Problem of the Firm

The present value of a filled vacancy by firm of productivity $y$ that employs worker with skill $x$ at wage $w$ is

$$J_t(w,x,y) = f(x,y) - w + \beta\Bigg[(1-\delta)(1-e^{\star}_{t+1}(w,x,y)\lambda(\theta_{t+1})J_{t+1}(w,x,y) + (1-\delta)e^{\star}_{t+1}(w,x,y)\lambda(\theta_{t+1})\Bigg[\Gamma_{t+1}(\tilde{y}_{t+1}(w,x,y))J_{t+1}(w,x,y) + \int_{\tilde{y}_{t+1}}^{y} J_{t+1}(\phi_{t+1}(x,y',y),x,y)\gamma_{t+1}(y')dy'\Bigg]\Bigg].$$

Using integration by parts we get

$$J_t(w,x,y) = f(x,y) - w + \beta(1-\delta)\Bigg[J_{t+1}(w,x,y) + e^{\star}_{t+1}(w,x,y)\lambda(\theta_{t+1})J'_{t+1}(\phi_{t+1}(x,y',y),x,y)\gamma(y')dy'\Bigg],$$

where $J'_{t+1}$ is the derivative of $J_{t+1}(\phi_{t+1}(x,y',y),x,y)$ with respect to $y'$.

The main decision the firm gives is how many vacancies to post each period:

$$\max_v v\lambda^f(\theta_t)\Bigg[\int u_t(x)J_t(\phi_t(x,0,y),x,y)dx + \int^y\int\int J_t(\phi_t(x,y',y),x,y)h_t(w,x,y')dwdxdy'\Bigg] - \kappa(v). \tag{12}$$

A vacancy can be filled by an unemployed worker or an employed worker. The first term inside the bracket is the expected return to vacancy that is filled by an unemployed worker while the second term is the expected return to vacancy filled by an employed worker. A firm with productivity $y$ can hire any worker employed at a firm with lower productivity $y' < y$ and pays the worker $\phi_t(x,y',y)$.

First order condition with respect to $v$ is

$$\lambda^f(\theta_t)\Bigg[\int u_t(x)J_t(\phi_t(x,0,y),x,y)dx + \int^y\int\int J_t(\phi_t(x,y',y),x,y)h_t(w,x,y')dwdxdy'\Bigg] = \kappa'(v). \tag{13}$$

At an interior optimum, firm equates the marginal cost of opening an extra vacancy to return to vacancy.

### E.7 Problem of the Worker

Now, we are in a position to define the value function for a worker.

First consider a worker with skill level $x$ employed at firm $y$ and earning $w$. Suppose she searches for a job with effort level $e$. The worker gets flow utility of $w - c(e)$ this period. Next period, with probability $\delta$ she becomes unemployed and earns lifetime utility of an unemployed worker, $U_{t+1}(x)$. With probability $(1-\delta)$ she remains employed and searches for a job. For a given effort level $e$, she does not meet with a firm with probability $1-\lambda(\theta_{t+1})e$ and her lifetime utility becomes $W_{t+1}(w,x,y)$. With probability $\lambda(\theta_{t+1})e$ she meets with a firm. With probability $1-\Gamma_{t+1}(y)$ the poaching firm has productivity $y' > y$. In this case the lifetime utility of the worker becomes $W_{t+1}(f(x,y),x,y)$. With probability $\Gamma(\tilde{y}_{t+1})$, the poaching firm has productivity $y' < \tilde{y}$. In this case, the lifetime utility of the worker remains as $W_{t+1}(w,x,y)$. If the poaching firm has productivity $y' \in [\tilde{y}_{t+1}, y]$, then his lifetime utility becomes $W_{t+1}(f(x,y'),x,y')$.

Hence, the lifetime utility of a worker with skill level $x$ employed at firm $y$ at wage $w$ is

$$\begin{aligned} W_t(w,x,y) = \; & \max_e w - c(e) + \beta \Bigg[ \delta U_{t+1}(x) + (1-\delta)[1-\lambda(\theta_{t+1})e] W_{t+1}(w,x,y) \\ & + (1-\delta)\lambda(\theta_{t+1})e \Big[ (1-\Gamma_{t+1}(y)) W_{t+1}(f(x,y),x,y) \\ & + \int_{\tilde{y}_{t+1}}^{y} W_{t+1}(f(x,y'),x,y') d\Gamma_{t+1}(y') + \Gamma_{t+1}(\tilde{y}_{t+1}) W_{t+1}(w,x,y) \Big] \Bigg]. \end{aligned} \tag{14}$$

Consider a worker employed at a firm $y$ with wage rate $f(x,y)$. Clearly, she has no gain from matching an outside firm, since no firm offers more than $W_{t+1}(f(x,y),x,y)$. In other words, optimal search effort for such worker is $0$. This implies that the lifetime utility for her is

$$W_t(f(x,y),x,y) = f(x,y) + \beta\delta U_{t+1}(x) + \beta(1-\delta) W_{t+1}(f(x,y),x,y). \tag{15}$$

Observe that state variables affect it through the value of unemployment. Since she does not search on the job, market tightness is irrelevant for on the job value. This implies that $y$ only effects it through the production function. Hence, the derivative of $W_t(f(x,y),x,y)$ with respect to $y$ is $f_y(x,y)/[1-\beta(1-\delta)]$.

Using integration by part and derivative of $W_{t+1}(f(x,y),x,y)$, the lifetime utility of an employed worker becomes

$$W_t(w,x,y) = \max_e w - c(e) + \beta \Bigg[ \delta U_{t+1}(x) + (1-\delta) \Big[ W_{t+1}(w,x,y) + \lambda(\theta_{t+1}) e \int_{\tilde{y}_{t+1}}^{y} \frac{f_y(x,y)}{1-\beta(1-\delta)} [1-\Gamma_{t+1}(y')] dy' \Big] \Bigg]. \tag{16}$$

Taking derivative with respect to $e$ gives us

$$c'(e) = \beta(1-\delta)\lambda(\theta_{t+1}) \int_{\tilde{y}_{t+1}}^{y} \frac{f_y(x,y)}{1-\beta(1-\delta)} [1-\Gamma_{t+1}(y')] dy'. \tag{17}$$

where he left hand side is the marginal cost of effort. The right hand side is the marginal return to search effort. $(1-\delta)\lambda(\theta)$ is the increase in the probability of meeting with a firm. The integral is the return to finding a match. $\beta$ is the discount factor. At the optimal solution, the cost of increasing the search effort should be equal to benefit of increasing the search effort.

Now consider unemployed worker. Unemployed worker has no choice, she searches for a job with effort level 1. In the current period she gets flow utility of unemployment $b(x)$. In the next period, with probability $\lambda(\theta)$ she finds a job. Given the assumption that firms can make take-it-or-leave-it offers to unemployed, finding a job does not increase lifetime utility. Hence, the lifetime utility of an unemployed worker with skill $x$ can be written as:

$$U_t(x) = b(x) + \beta U_{t+1}(x). \tag{18}$$

## E.8 Distribution Accounting

In this section, we derive how the distribution of workers over employment status changes over time.

First, consider distribution of unemployed: $u_t(x)$. $\lambda(\theta_t)$ fraction find a job and leave unemployment. $\delta$ fraction of employed workers with skill level $x$ separate from their job and become unemployed. Hence, unemployment distribution evolves according to

$$u_{t+1}(x) = u_t(x) - \lambda(\theta_t) u_t(x) + \delta \int \int h(w,x,y) dw dy. \tag{19}$$

Similarly, employed distribution evolves according to

$$\begin{aligned} h_{t+1}(w,x,y) = h_t(w,x,y) - \delta h_t(w,x,y)\lambda(\theta_t)[1-\Gamma_t(\tilde{y})] \\ + \int e_t(w',x,\hat{y}(x,w))\lambda(\theta_t)\gamma_t(y)h_t(w',x,\hat{y}_t(x,w))dw' \\ + \int^w e_t(w',x,y)\lambda(\theta_t)\gamma_t(\hat{y}_t(x,w))h_t(w',x,y)dw' + 1\{w \\ = \phi_t(x,0,y)\}u_t(x)\gamma_t(y), \end{aligned} \tag{20}$$

where $\hat{y}_t(x,w)$ satisfies $\phi_t(x,\hat{y}_t(x,w),y) = w$.

### E.9 Equilibrium

**Definition** For given initial distributions $u_0(x)$ and $h_0(w,x,y)$, a competitive equilibrium is a set of value functions $\{U_t(x), W_t(w,x,y), J_t(w,x,y)\}_t$, policy functions $\{e_t^\star(w,x,y), v_t^\star(y)\}_t$ prices $\{\phi(x,y,y')_t\}$, market tightness $\{\theta_t\}_t$ and distributions $\{u_t(x), h_t(w,x,y)\}_t$ such that

- Value functions solve (18), (16), (E.6),
- policy functions solve (13), (17),
- $\phi(x,y,y')$ is the wage rate that solves $W(f(x,y),x,y) = W(w,x,y')$, and $\phi(x,0,y)$ is the wage rate that solves $U(x) = W(w,x,y)$,
- market tightness is given by (11),
- distributions evolve according to (19) and (20).

## F Additional Analysis

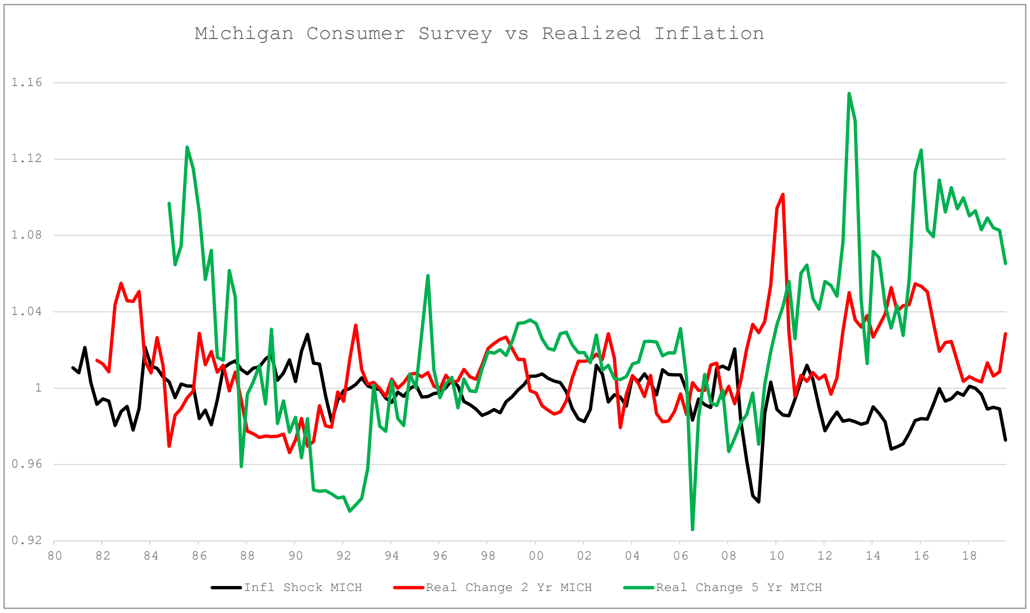


Figure 10: The Discrepancy Between the MCS Forecast and Realized Inflation The x axis refers to the calendar year. The black line represents the difference between the 1-year ahead MCS forecast and the realized inflation. The values above 1 indicate inflation exceeded forecasts. The red line represents the cumulative real wage loss for a worker who signed his contract two years ago, based on MCS forecasts. The green line represents the cumulative real wage loss for a worker who signed his contract five years ago, based on MCS forecasts.

Table 3: VAR(12) Analysis

Panel A: CPI Inflation Granger-causes Job-to-Job Transition Rate

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| Res.Df | 2 | 249.000 | 8.485 | 243 | 246 | 252 | 255 |
| Df | 1 | −12.000 | | −12.000 | −12.000 | −12.000 | −12.000 |
| F | 1 | 2.032 | | 2.032 | 2.032 | 2.032 | 2.032 |
| Pr(>F) | 1 | 0.022 | | 0.022 | 0.022 | 0.022 | 0.022 |

Panel B: Job-to-Job Transition Rate Granger-causes CPI Inflation

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| Res.Df | 2 | 249.000 | 8.485 | 243 | 246 | 252 | 255 |
| Df | 1 | −12.000 | | −12.000 | −12.000 | −12.000 | −12.000 |
| F | 1 | 0.850 | | 0.850 | 0.850 | 0.850 | 0.850 |
| Pr(>F) | 1 | 0.599 | | 0.599 | 0.599 | 0.599 | 0.599 |

(a) The results from the Granger Causality test with the null hypothesis of no explanatory power. Job-to-Job transition rates are from CPS and the inflation rates are computed from the CPI index of the BLS. The data is monthly and covers from 09/1995 to 12/2018. See Appendix **??** for details of the data sources.

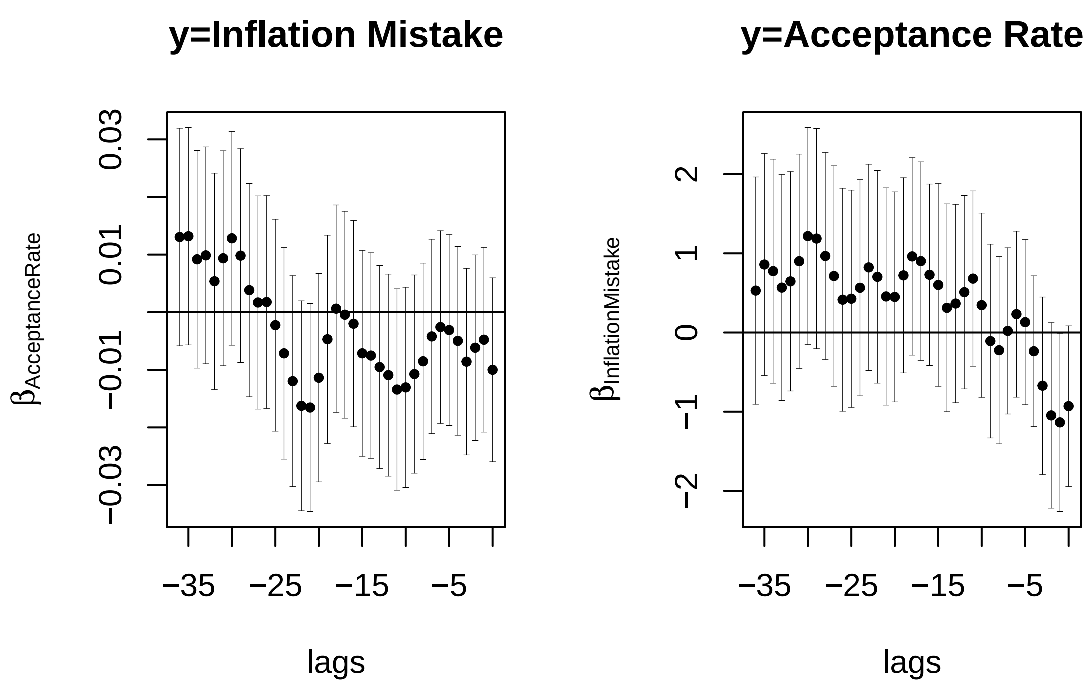


Figure 11: The left panel presents the coefficient estimates and the associated 95% CI for $\beta$ where 'inflation mistake' is regressed on the 'acceptance rate' with the specification in Equation 1. Each point and the bar correspond to an estimate where the regressors are with the associated lag in the x-axis. The right panel provides the same plot where the 'acceptance rate' is regressed on the 'inflation mistake'. See Appendix **??** for details of the data sources.

Table 4: VAR(12) Analysis

Panel A: Inflation Mistake Granger-causes Job-to-Job Transition Rate

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| Res.Df | 2 | 249.000 | 8.485 | 243 | 246 | 252 | 255 |
| Df | 1 | −12.000 | | −12.000 | −12.000 | −12.000 | −12.000 |
| F | 1 | 1.879 | | 1.879 | 1.879 | 1.879 | 1.879 |
| Pr(>F) | 1 | 0.038 | | 0.038 | 0.038 | 0.038 | 0.038 |

Panel B: Job-to-Job Transition Rate Granger-causes Inflation Mistake

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| Res.Df | 2 | 249.000 | 8.485 | 243 | 246 | 252 | 255 |
| Df | 1 | −12.000 | | −12.000 | −12.000 | −12.000 | −12.000 |
| F | 1 | 0.832 | | 0.832 | 0.832 | 0.832 | 0.832 |
| Pr(>F) | 1 | 0.617 | | 0.617 | 0.617 | 0.617 | 0.617 |

(a) The results from the Granger Causality test with the null hypothesis of no explanatory power. Job-to-Job transition rates are from CPS, the inflation rates are computed from the CPI index of the BLS and the inflation expectations are from Survey of Consumers from University of Michigan. The data is monthly and covers from 09/1995 to 12/2018. See Appendix **??** for details of the data sources.