The Labor Market Power Channel of Monetary Policy*

Anastasia Burya † Rui C. Mano‡ Yannick Timmer § Anke Weber¶

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Abstract

Using more than 250 million online vacancy postings, we study the interaction between labor market power and monetary policy. Empirically, we find that vacancy postings are significantly more responsive to monetary policy shocks for firms that have substantial labor market power, while their wage response is the same as for other firms. Vacancies that do not require a college degree or technology skills react more to monetary policy, especially when firms have labor market power. A search and matching model in which firms can attract workers by either offering higher wages or posting more vacancies can generate the patterns we uncover in the data. Our results help explain the "wageless" recovery after the 2008 financial crisis and the flattening of the wage Phillips Curve, especially for the low-skilled, who saw stagnant wages but a robust decline in unemployment.

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†Columbia University: ab4533@columbia.edu (Job Market Candidate)

‡International Monetary Fund: rmano@imf.org

§Federal Reserve Board: yannick.timmer@frb.gov

¶International Monetary Fund: aweber@imf.org

1 Introduction

In recent business cycles, wages seem to have become less reactive, while employment adjusted faster. For instance, in the period following the global financial crisis (GFC) unemployment declined steadily, especially among less-skilled individuals, while wages remained stagnant, just as monetary policy was extremely accommodative. Such a "wageless" recovery has been linked to the flattening of the Philips curve, see Galí and Gambetti (2019) and Figure 1, and has puzzled policymakers and academics alike, delaying interest rate increases and pointing to uncertainty about the level of the natural rate of unemployment. Ultimately the Federal Reserve revised its framework to put less emphasis on the natural rate of unemployment and instead more on actual employment outcomes, including across the distribution (Powell et al., 2020).

Labor market power may be related to the observed flattening of the wage Philips curve. U.S. firms are well known to have significant labor market power, which imposes substantial welfare losses (Hershbein et al., 2022; Berger et al., 2022). When firms have substantial bargaining power over workers, wages deviate from the marginal product of labor, i.e. there is a so-called markdown. The transmission of monetary policy to wages depends on whether the response of the marginal product of labor is passed through to wages, which in turn depends on the markdown itself. This suggests that labor market power may have potential implications for the relative transmission of monetary policy across labor and capital, and thus on the distribution of income.

In this paper, we aim to understand to what extent labor market power could help explain why accommodative monetary policy was successful in lowering the unemployment rate, especially for the low-skilled, without a material increase in wages.

To guide our empirical analysis, we build a simple search and matching model in which firms can attract more workers by either posting higher wages or more vacancies. This is because workers value earnings conditional on having a job but also value a higher probability of finding a job. In this environment, firms with labor market power can raise wages less in response to a positive demand shock, and instead, post more vacancies and hire more. This outcome relies on labor market power being associated with either more efficient job matching, e.g. due to vacancies from high market power firms being more visible, or lower costs of posting vacancies, e.g. due to fixed costs of recruiting and size effects.

To test the predictions of the model, we employ the near universe of online job postings provided by Burning Glass Technologies (BGT) to study how the transmission of monetary policy is affected by the presence of labor market power. The BGT data covers 250 million online job vacancy postings, and includes information on the firm, location, posted date, job requirements and offered wage, among other details. The highly disaggregated data allows us to construct firm-region specific market shares, which serve as our measure of labor market power. We combine this data with unexpected high-frequency monetary policy shocks around FOMC meetings.

We find that accommodative monetary policy shocks significantly increase the number of vacancies posted. The positive effect of accommodative monetary policy on labor demand, as measured by new vacancy postings, is amplified for firms that have more labor market power, even after controlling for unobserved and observed time-varying regional and firm characteristics, ruling out many other potential channels unrelated to labor market power. Quantitatively, a firm at the 50th percentile of labor market power increases its labor demand by $\approx 7\%$ in response to a 10 basis point surprise monetary loosening while a firm at the 95th percentile of the labor market power distribution increases labor demand by $\approx 9\%$. Moreover, the effect of monetary policy shocks on firms with market power is much more persistent, with effects remaining large and significant at least for eight quarters. A simple back-of-the-envelope calculation attributes up about one-quarter of the cumulative response of vacancies to monetary policy shocks after four quarters to observed labor market power. Due to the more persistent response of the high labor market power firms, after eight quarters, the contribution of labor market power is even larger, reaching almost 70%.

Moreover, these effects of labor market power are more pronounced for low-skilled vacancies. The amplification of labor demand effects of labor market power in response to monetary policy is particularly significant for vacancies that do not require a college degree or tech skills. Wages do not seem to be more responsive. These patterns are consistent with aggregate trends between 2010 and 2019 when the unemployment rate, particularly for low-skilled individuals, fell quite significantly, but wage growth was tepid, particularly for the less skilled, with a flat wage Phillips curve (Figure 1).

Our measure of labor market power follows the workhorse model of Cournot competition in which market power can be expressed as the market share for each firm.[1] This is computed by cumulating vacancy postings of a firm within a commuting zone relative to the cumulated vacancy postings across all firms in the same commuting zone. The advantage of this measure is that we do not rely on various structural assumptions, such as consumer preferences or production technologies. Moreover, this measure does not rely on additional data which is only available for publicly traded firms, which could potentially bias our sample significantly. We show that firms that have a larger market share pay significantly lower wages even conditional on a battery of job characteristics, such as the occupation and requirements for education, software, experience, etc. This negative correlation between market share and wages provides assurance that the market share

[1]See Atkeson and Burstein (2008).

indeed reflects market power and mitigates the concern that higher market shares may reflect other factors.

Literature Our paper relates to the work on jobless recoveries and job polarization (Jaimovich and Siu, 2020). Somewhat counter-intuitively, less labor market power would render accommodative monetary policy less effective in fighting the jobless recovery and job polarization after economic crises. However, labor market power can dampen the effectiveness of loose monetary policy in stimulating wage growth, especially for the low-skilled.

Our paper most closely relates to the literature on the effects of monetary policy on the labor market. Several early papers have established a strong response of unemployment to monetary policy shocks, such as Romer and Romer (1989). More recent papers focused on the mechanisms by which monetary policy transmits into labor markets, and their implications for inequality (Fornaro and Wolf, 2021; Coglianese et al., 2021; Dolado et al., 2021; Coibion et al., 2017; Andersen et al., 2021; Jasova et al., 2021; Bartscher et al., 2021; Bergman et al., 2022). For instance, Jasova et al. (2021) study the effects of increasing investment on employment. They find that firms that are less financially constrained tend to respond more both in terms of their investment and hiring.

Most household income is composed of wages, hence the effects of monetary policy on labor markets are especially important to study, particularly in light of the rising concern with monetary policy's distributional effects. Some papers, such as Andersen et al. (2021) emphasize the differential reaction of labor income and capital income. While reaction of the labor income remains roughly the same for the top 50% of the households, the reaction of the capital income is considerably larger for the top 1%, up to two times the reaction of the labor income, ensuring that this group gains the most from the Monetary Policy easing. Similarly, see De Giorgi and Gambetti (2017) for the effects of technology shocks. Others, for instance, Dolado et al. (2021) draw a connection to the differential effects on the different categories of labor. The authors develop a model with capital-skill complementarity and show that in this model high skilled workers' wages are more responsive to the monetary policy shocks, which means that a monetary policy easing increases the labor income inequality.

Our paper differs from this recent literature because we study the effect of labor market power on the transmission of the monetary policy. We also focus on inequality concerns due to the direct connection between higher labor market power and lower wages.

Market power and its effects on macroeconomic dynamics is a subject of growing interest. The literature focuses almost exclusively on product market power, such as (De Loecker et al., 2020), Wang and Werning (2020), Baqaee et al. (2021) and the books by Philippon (2019) and Eeckhout (2021). It has been shown that the recent rise in product market power can be responsible for several recent macroeconomic trends, most notably, for the flattening of the Phillips Curve, and can matter for the transmission of monetary policy (Duval et al., 2021; Ferrando et al., 2021; Kroen et al., 2021). Our paper differs from this literature in various respects. First, we study labor instead of product market power. Second, these papers do not study the consequences for labor markets (i.e. wages and employment) and instead focus on investment, stock prices, and firm financing. Third, product market power is more naturally a firm-level concept, while labor market power is regional due to the local nature of labor markets. We exploit this local variation both in terms of the definition of labor market power and when studying its consequences. Several papers in this literature also focused on the significant differences in the effects of monetary policy in economies with and without market power, with Wang and Werning (2020) and Baqaee et al. (2021) being the most notable examples. For instance, both papers document that the rise in product market power is one of the mechanisms behind the recent flattening of the price Phillips Curve.

There is also great interest in labor market power, with notable examples of (Berger et al., 2022; Hershbein et al., 2022; Azar et al., 2019a,a,b, 2020, 2022; Benmelech et al., 2022). However, unlike the literature on product market power, labor market power has not yet been connected to macroeconomic trends or monetary policy transmission, e.g. to the "wageless recovery". Additionally, it was recently documented that, similarly to the flattening of the price Phillips Curve, there was a flattening in the wage Phillips Curve (Galí and Gambetti (2019), Costain et al. (2022), Leduc and Wilson (2019); Daly and Hobijn (2014)). Leduc and Wilson (2019) find substantial evidence of a flattening of the wage PC during the recovery from the Great Recession, using both U.S. state and city panel data. Most papers link this flattening to downward rigidities and sluggish wage adjustments especially at low inflation levels. However, similarly to the role played by product market power, labor market power could also be a driving force behind this trend.

Finally, our paper relates to the literature that uses the Burning Glass Technologies (BGT) dataset. BGT is among the best established datasets for vacancy postings. Papers that specifically looked at labor market power using this dataset include Hershbein and Kahn (2018); Hazell et al. (2021); Hershbein et al. (2022); Azar et al. (2022). Those papers mostly focus on the equilibrium effects of labor market power, such as the levels of wages, and do not explore the role of labor market power in response to monetary policy.

This paper is organized as follows: Section 2 lays out a search and matching model that previews possible differential effects of labor market power on vacancies and wages. Section 3 introduces our data and Section 4 details our empirical approach and results. Finally, Section 5 concludes.

2 Model

This section introduces a simple search and matching model and lays out conditions under which vacancies respond more to shocks than wages for firms with labor market power.

Consider a stylized economy where firms can post wages (w) and vacancies (v) in separate labor markets. Hiring is represented by a function $h = h(w, v, HH) = \phi\left(\frac{v}{u}\right)u$, where the probability of a worker finding a job is $\phi\left(\frac{v}{u}\right)$ and $\frac{v}{u}$ denotes market tightness, or the ratio of vacancies v and unemployment u. Note that for now we do not model the hiring function explicitly, but such a function arises commonly in search and matching models.

The intuition to the presence of a hiring function is the fact that workers can choose which markets to search for a job. The value of searching in a particular market depends positively on wages and on the probability of finding a job.

In our case, the hiring function can be thought of as a representation of labor supply. It follows several common assumptions. First, the non-negative response of hiring to both wages and vacancies $h'_w, h'_v \geq 0$. Second, responses for both wages and vacancies are decreasing $h''_w, h''_v \leq 0$. And finally, the response of hiring to vacancies is increasing in wages $h''_{wv} \geq 0$.

Moreover, we would specifically require that both vacancies and wages strictly increase the number of new hires $h'_w, h'_v > 0$, so that firms, when adjusting their hiring decisions, can choose between two margins of adjustment — adjusting wages and/or vacancies. Posting higher wages would understandably allow the firm to attract more hires for any given level of vacancies. On the other hand, higher wages are costly since they increase the firm's payroll. Posting more vacancies would also allow increased hiring, because it raises the probability that a worker finds a job, but it also carries costs associated with posting vacancies. The latter is represented by a constant marginal cost, c.

For the baseline model, we make an additional simplifying assumption that the firm has to rehire each of its workers every period. This makes each firm's problem static.

As of now we do not make any specific assumptions about firms' demand structure and focus solely on the hiring problem. The only product demand parameter relevant for a firm's problem is its marginal revenue with respect to labor, denoted by MRL.

We assume that the production function takes one input only, and follows constant returns to scale.

Firm-level heterogeneity in terms of labor market power and ease of hiring can be represented in the model in several ways. One way would be to incorporate this heterogeneity directly into the hiring function with higher market power firms being able to match with higher probability to workers. This can be attributed to a higher awareness of workers of these firms, i.e. due to higher visibility of their vacancies. Another way would be to consider the difference in costs for posting vacancies with larger firms having lower costs. For now, we follow this second approach and leave the first for the next version of this draft.

In this environment, each firm's problem is a profit maximization such that:

$$\begin{aligned}
&\max_{w,v} profits = py - wl - cv \\
&s.t.\ l = h \\
&\qquad h = h(w, v, HH) \\
&\qquad y = al \\
&\qquad p = p(y)
\end{aligned}$$

The first order conditions to this problem are:

$$\begin{aligned}
&\frac{h'_v}{h'_w} = \frac{c}{h} \\
&w = \frac{\xi^w}{\xi^w + 1} MRL \\
&MRL = (py)'_l \\
&\xi^w = h'_w \frac{w}{h}
\end{aligned}$$

As discussed above, MRL is the marginal revenue of labor. Note that it is given by the product of the marginal revenue and the marginal product of labor: $MRL = (py)'_l = MR \times MPL$.

Note additionally that ξ^w is this model's equivalent of the usual labor supply elasticity and the formula for the optimal wage coincides with that of standard labor market power models without vacancy posting considerations. As in those models, the fraction $\frac{\xi^w}{\xi^w+1} < 1$ can be referred to as the markdown and can be interpreted as the degree by which wages deviate from those of competitive labor markets.

The new optimality condition in this model is the one representing the trade-off between posting more vacancies and higher wages and requiring that firms are indifferent between posting more vacancies

$$\frac{h'_v}{h'_w} = \frac{c}{h}$$

where c is the marginal cost of posting a vacancy. Recall that higher market power firms in this model are assumed to have lower vacancy posting costs. This condition then highlights the difference between different kinds of firms. Due to the assumptions that the hiring function is subject to decreasing returns to scale in either w or v, this expression shows that firms with larger marginal costs of hiring (those with lower labor market power under our interpretation), post fewer vacancies and offer higher wages.

We turn to the analysis of a one-time unexpected shock in this economy. First, recall that $MRL = MR \times MPL$. Note that any aggregate demand shock would manifest in an increase in MR and hence MRL. Note additionally that any productivity shock would result in an increase in MPL and hence MRL. In this simplistic model, there is no capital in the production function, and so any effect of the shock on the capital stock is embedded in the productivity term of the production function. Hence, any shock that increases the capital stock held by the firms would also result in an increase in MPL and hence MRL.

A monetary policy in this model can therefore be thought of as impacting the MRL as it combines in itself the positive effects on the aggregate demand and positive effects on the capital stock held by firms (increasing investment due to cheaper financing, for example). Moreover, note that there would not be any additional effects of a monetary policy shock if the firm's problem is static and if there is no effect of the monetary policy on household's labor supply.

Following a monetary policy shock, the FOC that relates wages and vacancies can be partially differentiated to get:

$$\underbrace{\frac{\partial w}{\partial MRL}\frac{MRL}{w}}_{\text{elast. of wages wrt. shock}} = \frac{ch''_{vw} - (h'_v)^2 - hh''_v}{hh''_{wv} + h'_v h'_w - ch''_w}\frac{\xi^v h'_w}{\xi^w h'_v} \underbrace{\frac{\partial v}{\partial MRL}\frac{MRL}{w}}_{\text{elast. of vacancies wrt. shock}} \tag{1}$$

Note that wages and vacancies change in the same direction if $ch''_{vw} > (h'_v)^2 + hh''_v$
Moreover, wages change by less than vacancies if $\xi^v < \xi^w$ and $hh''_v > -(h'_v)^2$

Prediction. In this environment, firms with high labor market power would post more vacancies but raise wages by less compared to firms with low labor market power following an accommodative monetary policy shock. This can be seen by taking the derivative with respect to c of the proportionality term between the two elasticities in equation (1), since in the model the marginal cost of posting vacancies is inversely related to labor market power. We now turn to the empirical analysis to examine whether this prediction is borne out in the data.

3 Data

3.1 Burning Glass Technologies

Burning Glass Technologies (BGT) data tracks all online vacancy postings from over 45,000 online job boards, carefully removes duplicates and cleans the data. The resulting dataset covers the near universe ($\approx 70\%$) of all U.S. online vacancy postings and comprises ≈ 250 million job vacancy postings for the years of 2007 and 2010-2019.

One advantage of this dataset is its extensive coverage. Unlike survey data, it is collected directly from firms' postings and therefore is an accurate representation of the vacancies in the economy. Concretely, it is free from the limitations of datasets that only cover firms of a certain size or firms that satisfy certain criteria, such as being publicly traded like Compustat.

All vacancies report an exact date when they were posted online, the name of the employer and the FIPS county code. This effectively allows BGT to be used as establishment-level data. For our analysis, we use Commuting Zones rather than counties as a closer approximation of local labor markets.

BGT data offers significant details on the type of vacancy. Breakdowns on the NAICS industry and ONET occupation levels are available. A large proportion of vacancies also lists job requirements, such as education or coding skills.

Education is reported for approximately half of vacancies. When education is missing, we impute it based on the data for the existing vacancies using the finest occupational breakdown. Effectively we assign the same education requirement within the same occupation. This procedure eliminates most of the missing values.

BGT vacancy data has several shortcomings originating from the way it is collected, especially in earlier years. The main concern is that online vacancy postings are not representative of all the postings in the economy with an overrepresentation of certain industries, such as IT or Education. However, robustness checks, for instance in Hershbein and Kahn (2018) indicate that, despite these shortcomings, the resulting vacancy data tracks aggregate and industry trends closely.

BGT additionally contains information about offered wages. The wage data is significantly less extensive with only 17% of the vacancies reporting wages. As noted in Hazell et al. (2021), this limitation does not preclude the data from being representative. The resulting wage data closely replicates many features of the occupation-level wage measures from other sources, even though, smaller firms and occupations with lower skill requirements are more likely to report wages in Burning Glass. Some occupations report a range of possible wages — in these instances, we take the midpoint of the range. For most of our analysis, we collapse vacancy-level data into an establishment-level panel with a breakdown at the firm-, commuting zone- and quarter-level.

3.2 Monetary Policy shocks

The baseline measure of monetary policy shocks we use is that developed in Jarociński and Karadi (2020). They focus on interest rate surprises in the three-month fed funds future, which exchange a constant interest for the average federal funds rate over the course of the third calendar month from the contract. As regular FOMC meetings are 6 weeks apart from each other, the three-month future reflects the shift in the expected federal funds rate following the next policy meeting. The implicit assumption is that changes to the balance sheet are orthogonal to changes in the policy rate (and that balance sheet measures would not affect the 3-month futures).

We prefer this measure because it provides a decomposition into pure monetary policy shocks and the Fed information component. The latter accounts for the fact that economic agents take Fed actions as a signal about the state of the economy and adjust their expectations accordingly. For instance, an expansion can be taken as a sign that the economy is performing poorly and as a result economic agents might, for instance, reduce investment. The effect of Fed information, therefore, goes in the opposite direction to that of monetary policy, and mixing the two together can significantly bias the results. As a baseline, we are only interested in the effect of the monetary policy shock and we use the information component as a control.

As a robustness check, we use several other measures of monetary policy shocks, including those of Nakamura and Steinsson (2018), Jarocinski (2021), and Bu et al. (2021). Nakamura and Steinsson (2018) use principle component analysis to combine all the horizons of the monetary policy, from one-month to two-year in one shock. It, therefore, allows capturing the effect of monetary policy on the whole yield curve. Jarocinski (2021) estimates four different shocks, including the standard monetary policy shock and the remaining shocks not affecting the near-term fed funds futures. The other shocks include an Odyssean forward guidance shock (a commitment to a future course of policy rates), a shock that affects the longer-term treasury yield and is most affected by asset purchase announcements, and a Delphic forward guidance shock (Campbell et al., 2012), which captures the stance of future monetary policy in the sense of a prediction of the appropriate stance of policy, rather than its commitment. Bu et al. (2021) include unconventional policy constructed through a Fama-MacBeth two-step procedure to extract monetary policy shocks from the common component of outcome variables. They conclude that their measure does not contain a significant central bank information effect. Please refer to Table A2 for the estimation results.

3.3 Definition of labor market power

For our baseline results, we measure labor market power with the share of vacancies posted by a single firm in a local labor market. The use of the firm's market share as a proxy for market power is justified theoretically, for instance in oligopsonistic settings or in some search and matching frameworks. In those types of models, the market share would determine the degree of impact of a single firm wage at the aggregate market wage capturing the fact that those firms are difficult to substitute away from. This would mean that the firms with a larger market share will have lower elasticity of labor supply and, subsequently would be able to pay lower wages.

In search and matching framework, similar to that of Jarosch et al. (2019). In this framework the fact that the firm has a larger market share increases the probability of a single worker coming across the same firm in the future. This gives the firms with larger shares more control over the worker's outside option and allows for stronger bargaining position, which results in lower wages.

We define a local labor market as a U.S. census commuting zone. This breakdown proves to be very fine with some of the smaller firms not having two subsequent periods of posting the same vacancies. To avoid losing the extensive number of observations, we use cumulative shares up to any given date. The additional advantage of this measure is the fact that it might correspond more closely to employment shares rather than vacancy shares.

$$\text{Market Share}_{i,c,t} = \frac{\sum_{\tau \leq t} v_{i,c\tau}}{\sum_{\tau \leq t} \sum_i v_{i,c\tau}}$$

Figure 2 plots the distribution of our measure of labor market power. On the left panel, we plot the distribution of the market share across firms. On the right-hand side, we plot the distribution of the 95th percentile market share across commuting zones. The average vacancy is exposed to the market share of 0.8%, median - 0.1%, p95 - 3.7%. We have in total over 15 million firm-commuting zone-time observations with a total of over 380,000 firms and over 700 commuting zones. The average commuting zone has postings from 22,000 firms. An average firm posts in 170 commuting zones (see Table 1 for further details). The market share is highly skewed with most firms having close to zero market shares, while a small share of firms has substantial market power.

Theoretically, higher labor market shares should correspond to lower wages. Figure 3 plots the average wage the firm posts on their vacancies on the y-axis and the labor market share of a firm in a commuting zone on the x-axis. To account for the right-skewed nature of the labor market share, the x-axis is on a log-scale. The left panel plots the relationship for non-college vacancies and the right panel for college vacancies. A large share of the labor market share distribution has an average posted wage that is relatively similar. In particular, firms that have a market share between 0 and 0.00005 post an average wage between US$50,000 and US$48,000 for non-college vacancies. The degree of market power these firms have is likely to be extremely low and not significantly different. A firm that has a market share of 0.00005 posts 1 out of 20,000 vacancies, which is unlikely to enable the firm to be in a better bargaining position. However, once a firm starts to control more than 0.005% of the market their posted wage declines strongly. For instance, a firm that has a market share of 0.1%, posting 1 in every 1000 vacancies, posts an average wage of less than US$45,000 for non-college vacancies.

The same pattern is visible for college vacancies as well, with posted wages declining more linearly than for non-college vacancies, but with a large drop in posted wages beyond a 0.005% market share. As expected, the overall level of wages posted is significantly higher at around US$76,000 for firms with "no" labor market power (market share $<$ 0.00005) and around US$70,000 for firms with labor market power (market share $>$ 0.001).

The negative relationship between labor market shares and wages could suffer from a spurious correlation and compositional biases. For instance, if firms with a higher labor market share hire less-skilled workers, the lower wages are not directly due to their labor market *power*. The split between college vs. non-college vacancies partly addresses the compositional issue, making only a within college/non-college comparison, but can not fully dismiss the compositional issue, as even within each category skill requirements and productivity can differ significantly.

In the previous literature, labor markets are sometimes not defined at the commuting zone-level, but rather at a finer level with additional industry-level breakdown. We check robustness to this alternative definition and find similar results. Please refer to Table A1 and Figure A1.

In addition to that, to measure Labor Market Power on the Commuting Zone level we use a concentration measure given by Herfindahl-Hirschman Index. This is a measure commonly used in the literature to access the competitiveness of a particular market. HHI is given by:

$$\text{HHI} = \sum_i (\text{Market Share}_{i,c,t})^2$$

We use this measure to access whether commuting zones where firms have more market power have flatter Phillips Curve.

4 Empirical results

This section documents that vacancies are more responsive to monetary policy shocks for firms with labor market power, while the response of wages does not seem to depend on labor market power. Moreover, there is significant heterogeneity across vacancy types — vacancies that do not require a college degree or tech skills react more to monetary policy in the presence of labor market power.

4.1 Monetary Policy, Labor Market Power and Vacancy Postings

To assess whether monetary policy shocks have a differential effect on posted vacancies depending on the extent of labor market power, we run the following specification:

$$\text{Log Vacancies}_{i,c,t} = \alpha + \beta_3 \text{ MP shock}_t \times \text{Labor Market Power}_{i,c,t-1} + X_{i,c,t} + \gamma_{i,t} + \gamma_{c,t} + \varepsilon_{i,c,t}$$

where $X_{i,c,t}$ includes the Federal Reserve information shock and its interactions with labor market share, $\gamma_{i,t}$ are firm-time fixed effects that absorb any firm-time variation like productivity, improved funding conditions, or changes in stock prices, as well as product market power which is often defined at the firm-level, $\gamma_{c,t}$ are commuting zone - time effects that absorb any time-varying regional shocks, such as local demand shocks.

Table 2 presents the results. In all columns, we find that vacancies of firms with labor market power are more responsive to monetary policy shocks (see Table 2). Moving from column 1 to column 7, we saturate the regression equation with additional fixed effects. Column 1 shows the results of subsection 4.1 without fixed effects. The exclusion of time fixed effects allows us to estimate the effect of a monetary policy shock on vacancies directly. The coefficient of the monetary policy shock is negative and statistically significant. The coefficient of -0.328 indicates that for a firm without labor market power vacancy postings fall by 3.48% in response to a 10 basis points contractionary monetary policy shock. The interaction between the monetary policy shock and lagged market share is also negative and statistically significant. The negative interaction term illustrates that labor market power amplifies the response of monetary policy shocks, i.e. firms that have a larger market share in a commuting zone reduce their vacancy postings by even more compared to a firm that has no labor market power. In column 2 we include firm fixed effects to our regression specification to control for unobserved and observed time-invariant heterogeneity on the firm-level, for instance, the average number of vacancies a firm posts during our sample period, and the results remain qualitatively unchanged. Column 3 introduces time fixed effects. The inclusion of time fixed effects has the advantage of exploiting variation across firms with differential degrees of labor market power at a given point in time, but as the coefficient on the monetary policy shock itself is collinear with the time fixed effect, we can only interpret the differential and not the total response to monetary policy. However, as in columns 2 and 3 the interaction term is negative and statistically significant. Column 3 introduces commuting zone fixed effects to column 2. The inclusion of the regional effects controls for potential time-invariant confounding factors at the regional level, such as the average income per capita during our sample period. The inclusion of commuting fixed effects leaves the results unchanged. Column 5 introduces firm, time, and commuting zone fixed effects simultaneously.

Column 6 introduces firm×time fixed effects to the regression specification. The introduction of firm×time fixed effects leads to a large reduction in the sample size from 15.7 million to 12.8 million observations, but an even larger drop in the number of firms in the sample from 354,254 to 199,893. The cost of the reduced sample size comes at the benefit of a tighter identification. The firm×time fixed effect controls for time-invariant (as in column 2) and time-variant factors that could affect our results. The regression implicitly compares the same firm in two different regions at the same point in time. Naturally, this requires a firm to be present in two regions at a given time leading to a large reduction in the sample size. However, comparing the same firm in two different regions can rule out various time-variant factors that are correlated with labor market power at the firm-level in driving our results. For instance, firms' financial constraints are likely time-varying but are firm-level rather than firm-region-level characteristics. Furthermore, firms that have a substantial amount of product-market power likely have product-market power on the national rather than the regional level.[2] Instead, labor markets are much more local, and therefore labor market power is also likely to be a local rather than a national characteristic. Therefore, column 6 allows us to identify the effect of labor market power in the transmission of monetary policy, conditional on time-variant variation in the product market power and financial constraint *of the same firm*.

Ultimately, column 7 saturates the regression specification with additional commuting-zone × time fixed effects to allow for within-commuting-zone-quarter fixed effects. The commuting-zone × time fixed effect controls for example for region-specific time-varying characteristics such as the concentration of vacancies and tests whether, conditional on the tightness of the regional labor market, firms with more market power respond differentially to monetary policy. As in the less saturated specifications, firms with more labor market power adjust their labor demand more compared to other firms. Since column 7 is the most saturated specification in which confounding factors that could drive our results are least likely, this is our preferred specification. Quantitatively, the interaction term between the monetary policy shock and the local labor market share is -7.895 and varies little relative to the other specifications (other than specification 1). The coefficient can be interpreted as follows. For a firm that controls 10% of the local labor market, vacancy postings rise by 7% more in response to a 10 basis point accommodative monetary policy shock relative to a firm that has no labor market power.

The results are also illustrated in Figure 4 with numerical examples. We use column

[2]For instance, De Loecker et al. (2020) measure product market power on the firm-level. Our results are also confirmed for tradable firms, for which firms' product market power is even more likely to be driven on the national or global rather than on the commuting zone level.

4 of Table 2 for the illustration as our aim is to understand both the interaction effect between labor market power and monetary policy, but also the total effect, which precludes us from using a specification with time fixed effects. On the y-axis, we plot the change in vacancy postings in response to a 10 basis point loosening of monetary policy, for three hypothetical firms at the 5th, 50th, and 95th percentile of the labor market share distribution. For firms at the 5th and 50th percentile of the distribution, the response of the change in vacancy postings is virtually the same at around 7%. The number is consistent with column 4 of Table 2. The strong similarity between the result for the 50th percentile and the 5th percentile reflects the fact shown in section 3 and Figure 2 that labor market power is extremely skewed. The vast majority of firms have almost no labor market power (including the median firm), but a small share of firms, that control by definition a large share of the market, have significant labor market power. The hypothetical firm at the 95h percentile increases its vacancy postings by 9% in response to a 10 basis point accommodative monetary policy shock, almost 30% more than firms without labor market power.

Until now we have only analyzed the contemporaneous effect of monetary policy on labor demand through vacancy postings. Next, we employ local projection methods in which we test for the persistency of the effects of monetary policy on labor demand and its interaction with labor market power.

We estimate the following equations:

$$\sum_{i=0}^{i=N} \text{Log Vacancies}_{i,c,t+i} = \alpha + \beta_{3,i}\ \text{MP shock}_t \times \text{Labor Market Power}_{i,c,t-1} + X_{i,c,t} + \gamma_{i,t} + \gamma_{c,t} + \varepsilon_{i,c,t}$$

where i reflects the quarterly horizon of vacancy postings. Figure 5 plots the estimated response of vacancy postings for a hypothetical firm with 100% labor market for different horizons. The response of vacancies of firms with labor market power is persistently different and increases over time compared to those that do not have labor market power following a monetary policy shock. Figure 6 explicitly compares the response of labor demand over time for the median firm in terms of labor market power to a firm with a high degree of labor market power (95th percentile). Both firms increase their labor demand strongly, peaking at one quarter after the surprise. The firm with a large degree of labor market power increases its demand by around 3% in response to a 10 basis point monetary policy loosening, while a firm with median labor market power increases its vacancy postings by only 2%. After the first quarter, both firms decrease their vacancy postings. However, for the firm with medium labor market power, the effect of monetary policy seems to be purely temporary, with the additional number of vacancy postings reaching close to zero after four quarters. In contrast, the firm with significant labor market power has still posted more vacancies over the four quarters after the shock compared to a scenario in which monetary policy would not have been active. The persistency for firms with labor market power indicates that employment is persistently and even permanently higher for a firm with labor market power after an accommodative monetary policy shock.

In what follows, we investigate the effects of labor market power across different types of job postings. BGT provides granular data on postings, including on skill and education requirements. We focus on two types of requirements. First, we differentiate between college vs. non-college vacancies. In our sample, $\approx 40\%$ are college vacancies. We also study the degree of tech-savviness of vacancies, by differentiating between vacancies that require software skills and those that do not, in the spirit of Acemoglu et al. (2021) who use Burningglass to identify AI vacancies. Vacancies that require software skills make up $\approx 28\%$ of all vacancies.

As one would expect, college vacancies and tech-savvy vacancies are strongly related to each other, with a correlation between the two vacancy types of $\approx 29\%$. We run the following specification:

$$\begin{aligned}\text{Log Vacancies}_{i,c,t,j} = \alpha + & \beta_3 \text{ MP shock}_t \times \text{Labor Market Power}_{i,c,t-1} + \\ & \beta_6 \text{MP shock}_t \times \text{Labor Market Power}_{i,c,t-1} \times \text{Type}_j + X_{i,c,t} \\ & + \gamma_{i,t} + \gamma_{c,t} + \varepsilon_{i,c,t}\end{aligned}$$

where Type_j is a dummy that takes the value of 0 or 1 depending on the characteristic of the job posting. We investigate effects across these types. The triple interaction coefficient β_6 captures whether there is significant heterogeneity across a particular type of vacancy. If the double interaction (β_3) has a different sign than the triple interaction (β_6), that would mean that the effect is weaker for the [Type = 1].

Table 3 shows the results. First, we show the differential response across vacancy types, discarding the effect of labor market power across different vacancies. Column 1 first confirms our base result that for the average vacancy labor market power strengthens the labor demand effect of monetary policy. We also shed light on whether monetary policy affects college vs. non-college vacancies differently. The interaction between the monetary policy shock and the vacancy type dummy is positive and statistically significant in column 1. In column 1 the vacancy type dummy is one if the vacancy is a college vacancy. As the effect of monetary policy is negative (contractionary monetary policy reduces labor demand), the positive interaction term implies that college vacancies respond less strongly to monetary policy than non-college vacancies.

Column 2 illustrates whether this effect is partly driven by labor market power. Indeed, the interaction between the monetary policy shock, market share and the vacancy type dummy is positive and statistically significant. The positive triple interaction term shows that labor demand effects of labor market power in response to a monetary policy shock are stronger for non-college vacancies. When interpreting the economic magnitude, we can see that the effect is around -7.8 for non-college vacancies and $(-7.8 + 2.9) = -4.9$ for college vacancies.

The results are similar for software-related vacancies. In column 3 we can see that software vacancies are less responsive to monetary policy in general, and when firms exhibit labor market power their adjustment seems to be done along the non-software dimension, rather than on the more tech-related vacancies.

4.2 Vacancy Postings and Employment

So far, we have established that vacancy postings are more responsive to monetary policy when firms have more labor market power. Ultimately, what matters for monetary policy is employment and not vacancy postings. Unfortunately, detailed granular employment data on the firm-region-level is not available. We therefore merge our BGT data with Compustat data for a large number of publicly traded firms to analyze the relationship between vacancy postings and employment growth. In particular, we aggregate vacancy postings to the firm-year level and fuzzy merge the BGT firm name to Compustat.[3]

We estimate the following regression equation:

$$\Delta Employment_{i,t} = \alpha_i + \alpha_t + \beta_1 \text{Log Vacancies}_{i,t} + \epsilon_{i,t} \tag{2}$$

where $\Delta Employment_{i,t}$ is the log change in employment of firm i between year t and $t-1$ in Compustat. Log Vacancies$_{i,t}$ is the log number of vacancies posted by firm i in year t from BGT. Log Vacancies$_{i,t}$ is defined in the same way as the dependent variable in subsection 4.1, which allows us under certain assumptions to translate the effect of monetary policy on vacancies to an effect on employment based on the elasticity estimated in Equation 2. Figure 7 shows the result of Equation 2 in a scatterplot. The relationship between number of vacancies and the percent change in employment is positive and statistically significant. Economically, a doubling in the number of vacancies Log Vacancies$_{i,t} = 1$ is associated with a 0.74 percentage point stronger employment growth.

Figure 6 shows that after four quarters, a firm with high labor market power increased their vacancy postings by a factor of 2 in response to a 100 basis point accommodative monetary policy shock. A firm with medium labor market power instead did not increase

[3]The quarterly version of Compustat does not have employment information, which is why we use the annual Compustat file.

their vacancy postings. Translating the vacancy postings into employment growth, we need to multiply the log number of vacancies created by the coefficient on the elasticity of employment growth to vacancies. Consequently, a firm with high labor market power has $(0.74 * 2 =)$ 1.48 percentage points stronger employment growth in response to the accommodative monetary policy shock. According to our estimates, a firm without labor market power does not exhibit stronger employment growth.

This back-of-the-envelope should be taken with a grain of salt, as it makes several strong assumptions. First, we only have employment data for listed firms. For the calculation to be accurate, the elasticity needs to be the same for firms that we merge with Compustat and the firms that we do not merge. Second, the elasticity of employment growth with respect to vacancy postings may vary between firms with and without labor market power. For instance, monopsonists may post more vacancies but do not increase their actual hiring in response to an accommodative monetary policy shock, as more employees leave when labor market becomes tighter in response to the shock. However, we do not find evidence in favor of a differential elasticity for firms with differential degree of labor market power, suggesting that higher vacancy postings of firms with labor market power also reflect more intense hiring and employment growth. Even for firm with a large degree of labor market power there is a strong relationship between vacancy postings and employment growth [4]

4.3 Monetary Policy, Labor Market Power and Wages

We run the same specification as equation (4.1) substituting the dependent variable for wages measured as deviations from the regional average wage. The resulting wage measure is given by:

$$\text{Wage Measure}_{i,c,t} = log(w_{i,c,t}) - log(\bar{w}_{c,t})$$

We then estimate the following regression:

$$\sum_{i=0}^{i=N} \text{Wage Measure}_{i,c,t+i} = \alpha + \beta_{3,i} \text{ MP shock}_t \times \text{Labor Market Power}_{i,c,t-1} + X_{i,c,t} + \gamma_{i,t} + \gamma_{c,t} + \varepsilon_{i,c,t}$$

We note that BGT data for wages is much less comprehensive since only $\approx 17\%$ of postings include either a minimum, a maximum or a rage for the wage offered. When a range is reported we take the average between the min and the max.[5] We find that labor market power does not affect deferentially the response of wages (Table 4).

[4]The positive relationship is robust to using other specifications, such as log-log equations.

[5]Hazell et al. (2021) suggests that employers pay the posted wages.

4.4 Labor Market Power and the Wage Phillips Curve

The strong effect of monetary policy on vacancy postings that likely translates into stronger employment growth (as argued in subsection 4.2) for firms with labor market power, but the absent effect on wages suggests that companies with a large degree of labor market power can hire more workers without increasing wages, as formalized in section 2.

This result raises the question whether monetary policy was unable to stimulate wage growth by reducing the unemployment rate, due to a flat wage Phillips curve. Figure 1 shows that the wage Phillips curve has flattened significantly and was particularly flat during the period between the global financial crisis and the Covid-19 crisis. The lower estimated negative coefficient in the time-series regression, however, can be explained by various factors that are not necessarily linked to labor market power.

In order to shed more light on whether labor market power can be at least partly responsible for the flatter slope of the wage Phillips curve, we estimate the wage Phillips curve on the commuting zone-level. Using wage growth data from BGT and unemployment rate data from BLS, we estimate the following regression equation:

$$\begin{aligned} \text{Wage Growth}_{c,t} = \alpha + \beta_1 \text{ Unemployment Rate}_{c,t} + \beta_2 \, \mathbb{1}\text{Labor Market Power}_{c,t} + \\ \beta_3 \text{Unemployment Rate}_{c,t} \times \mathbb{1}\text{Labor Market Power}_{c,t} + \epsilon_{c,t} \end{aligned} \tag{3}$$

where Wage $\text{Growth}_{c,t}$ is the annual wage growth of posted vacancies from Burning Glass Technology at the commuting zone-year level. $\mathbb{1}$Labor Market $\text{Power}_{c,t}$ is a dummy that is equal to one if the commuting zone has an HHI index based on vacancy postings above the median and zero otherwise. Unemployment $\text{Rate}_{c,t}$ is the unemployment rate from BLS at the commuting zone year-level.

Figure 8 shows the commuting zone-level wage Phillips curve graphically in the form of a binscatter based on the regression Equation 3. For commuting zones that have a below median HHI in terms of vacancy postings, labelled as *Low Labor Market Power* by the blue diamonds, the wage Phillips curve is steep, i.e. there is a strong negative relationship between the unemployment rate at the commuting zone-level and wage growth based on BGT data. However, when zeroing into commuting zones with *High Labor Market Power*, i.e. where the HHI of vacancy postings is above the median, there is no association between the unemployment rate and wage growth.

The results are confirmed in Table 5, where we show the regression Equation 3 with varying levels of fixed effects included. The coefficient β_1 reflects the wage Phillips curve for regions where labor market power is low. The coefficient is always negative and statistically significant, ranging widely from -1.5 to -5.3, depending on the level of fixed effects introduced. The change in the coefficient in response to the saturation of the regression model with fixed effects indicates that commuting zone and time specific factors that are correlated with the unemployment rate are important to control for when attempting to interpret the wage Phillips curve causally. For instance, inflation expectations are likely to be captured by the time fixed effects (Hazell et al., 2022), which may bias the coefficient. To identify the effect of labor market power on the slope of the Phillips curve we focus on the interaction between the unemployment rate and a dummy that is one if there is significant concentration of vacancy postings in the commuting zone, as measured by the HHI, following, e.g. Azar et al. (2020). The coefficient on the interaction between labor market power and the unemployment rate is positive and statistically significant, leading to an entirely flat or flatter (depending on the specification) wage Phillips curve.

Overall, this result suggests that labor market power flattens the wage Phillips curve and serves as an explanation why accommodative monetary policy in the presence of labor market power can significantly stimulate labor demand but does not lead to a strong increase in wages.

5 Conclusion

In this paper, we have used the near universe of online vacancy postings to study the transmission of monetary policy to labor demand. In particular, we are interested in whether labor market power changes the transmission mechanism of monetary policy to the labor market. We find striking evidence that labor market power strengthens the effect of monetary policy on labor demand. Empirically, our results show that a firm with more labor market power in a certain region expands its vacancy postings more relative to its counterparts. In contrast, we do not find that the response of wages to monetary policy depends on labor market power.

To get an understanding of how important this effect is for the observed dynamic, we estimate the counterfactual vacancy response with a relatively simple back-of-the-envelope calculation. We use the estimated coefficients for the monetary policy shock and the interaction between the monetary policy shock and the labor market power measure. The counterfactual for the no labor market economy is obtained by equating the labor market power measure to zero for all of the firms. The response for the economy with the actually observed levels of market power is calculated by substituting in the actual labor market power measures from the data. The same procedure is performed for the contemporaneous quarter and up to 9 quarters ahead. The resulting effect for the number of vacancies generated is given in Figure 9. The resulting cumulative effect is given in

Figure 10. The latter allows us to calculate which share of all vacancies posted up to date are due to labor market power. For the four-period ahead calculation approximately 25% can be attributed to the presence of labor market power. Due to more persistence in the response for larger labor market power firms, for the 9-period ahead calculation, this number rises as high as 68%. Both those calculations, while not perfectly reliable, suggest a strong effect of labor market power on the macroeconomy.

We detect significant heterogeneity across vacancy types. Vacancies that require a college degree and those tailored toward "tech-related" workers are far less responsive to monetary policy than those that do not require a college degree and are targeted towards non-tech workers. The results imply significantly more heterogeneity in labor demand for less and large swings in inequality across the monetary policy cycle, as we have seen in the past.

Our results have important implications for policy. First, our results can partly explain why before the Covid-19 crisis the unemployment rate declined significantly, but wages lagged behind. We build a model that predicts that firms with labor market power can hire more workers by posting more vacancies without increasing the wage. The slow response in wages during the period of monetary expansion before the Covid-19 crisis, therefore, does not imply that the unemployment rate was above the natural rate, but instead indicates a flat wage Phillips curve relationship.

Going forward, contractionary monetary policy will likely hurt regions and workers more where labor market power is strong. However, the strong and negative effects on labor demand do not necessarily imply that wage growth will slow down significantly, as firms with significant labor market power are more likely to adjust their wage bill through the number of employees rather than through lowering wages.

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Table 1: Summary of the Panel Structure

	Total	Firms	Commuting Zone	Time
Number of Observations	15,810,352	387,107	708	43
Average Number of Firms	387,107	-	22,412	103,230
Average Number of CZ	708	170	-	704
Average Number of Periods	43	29	42	-

This table reports the number total number of observations and the number of observations across the time and geographical dimensions of the data

Table 2: Labor Demand Effect of Monetary Policy

	Log Vacancies$_{i,c,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MP Shock$_t$	-0.348***	-0.661***		-0.715***			
	(0.007)	(0.006)		(0.006)			
Market Share$_{i,c,t-1}$	23.160***	14.538***	14.958***	20.362***	20.866***	21.439***	22.713***
	(0.849)	(0.526)	(0.537)	(0.662)	(0.674)	(0.761)	(0.748)
MP Shock$_t\times$ Market Share$_{i,c,t-1}$	-13.935***	-3.289***	-5.439***	-5.296***	-7.624***	-8.722***	-7.895***
	(1.829)	(1.143)	(1.165)	(1.413)	(1.442)	(2.249)	(2.245)
Obs.	15,092,441	15,070,026	15,070,026	15,070,026	15,070,026	12,851,844	12,851,727
Firm FE		✓	✓	✓	✓		
Time FE			✓		✓		
CZ FE				✓	✓	✓	
Firm*Time FE						✓	✓
CZ*Time FE							✓
No. Firms	377669	355254	355254	355254	355254	199839	199839

This table reports results for the following regression: Log Vacancies$_{i,c,t}$ $= \alpha + \beta_3$ MP shock$_t$ $\times$ Labor Market Power$_{i,c,t-1} + X_{i,c,t} + \gamma_{i,t} + \gamma_{c,t} + \varepsilon_{i,c,t}$, where Log Vacancies$_{i,c,t}$ is defined as the log number of vacancies posted by firm i, in commuting zone c in quarter t. MP shock$_t$ is the monetary policy shock by Jarociński and Karadi (2020), in which a positive value reflects monetary policy tightening. Labor Market Power$_{i,c,t-1}$ is defined as the cumulative labor market share of firm i in commuting zone c at quarter $t-1$. For more details see section 3. $\gamma_{i,t}$ are firm-time, $\gamma_{c,t}$ are commuting-zone(CZ)-time fixed effects. Standard errors are double clustered at the firm and commuting zone level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Labor Demand Effect of Monetary Policy across Vacancy Types

	Log Vacancies$_{i,c,t,j}$			
	(1)	(2)	(3)	(4)
Market Share$_{i,c,t-1}$	18.033***	19.173***	18.380***	21.736***
	(0.603)	(0.638)	(0.630)	(0.711)
MP Shock$_t \times$ Market Share$_{i,c,t-1}$	-6.419***	-7.785***	-7.424***	-8.701***
	(1.550)	(1.698)	(1.556)	(2.018)
Vacancy Type$_j$	-0.156***		-0.233***	
	(0.002)		(0.002)	
MP Shock$_t \times$ Vacancy Type$_j$	0.368***		0.187***	
	(0.011)		(0.013)	
Market Share$_{i,c,t-1} \times$ Vacancy Type$_j$		-2.286***		-7.932***
		(0.198)		(0.320)
MP Shock$_t \times$ Market Share$_{i,c,t-1} \times$ Vacancy Type$_j$		2.938***		3.576**
		(0.963)		(1.457)
Obs.	17,342,560	17,342,560	16,277,587	16,277,587
Vacancy Type	college	college	software	software
Firm*Time FE	✓	✓	✓	✓
CZ*Time FE	✓	✓	✓	✓
Vac. Type*Time FE		✓		✓

This table reports results for the following regression: Log Vacancies$_{i,c,t,j}$ $= \alpha + \beta_3$ MP shock$_t$ $\times$ Labor Market Power$_{i,c,t-1}$ $+ \beta_6$MP shock$_t$ $\times$ Labor Market Power$_{i,c,t-1}$ $\times$ Type$_j$ $+ X_{i,c,t} + \gamma_{i,t} + \gamma_{c,t} + \varepsilon_{i,c,t}$, where Log Vacancies$_{i,c,t}$ is defined as the log number of vacancies posted by firm i, in commuting zone c in quarter t. MP shock$_t$ is the monetary policy shock by Jarociński and Karadi (2020), in which a positive value reflects monetary policy tightening. Labor Market Power$_{i,c,t-1}$ is defined as the cumulative labor market share of firm i in commuting zone c at quarter $t-1$. Type$_j$ is a dummy taken the value of one if the vacancy requires a college degree/software skills and zero if the the vacancy does not require a college degree/software skills. For more details see section 3. $\gamma_{i,t}$ are firm-time, $\gamma_{c,t}$ are commuting-zone(CZ)-time fixed effects. Standard errors are double clustered at the firm and commuting zone level. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Wage Effect of Monetary Policy

	Log Wages$_{i,c,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MP Shock$_t$	-0.001	-0.146***		-0.149***			
	(0.008)	(0.006)		(0.006)			
Market Share$_{i,c,t-1}$	0.277***	-0.084*	-0.011	0.056	0.112***	0.354***	0.390***
	(0.055)	(0.047)	(0.049)	(0.042)	(0.043)	(0.050)	(0.055)
MP Shock$_t \times$ Market Share$_{i,c,t-1}$	-0.192	0.579**	-0.009	0.498**	-0.090	-0.433	-0.363
	(0.247)	(0.239)	(0.245)	(0.238)	(0.243)	(0.348)	(0.435)
Obs.	3,611,431	3,546,366	3,546,366	3,546,366	3,546,366	2,716,562	2,715,673
Firm FE		✓	✓	✓	✓		
Time FE			✓		✓		
CZ FE				✓	✓	✓	
Firm*Time FE						✓	✓
CZ*Time FE							✓
No. Firms	281380	216315	216315	216315	216315	97858	97856

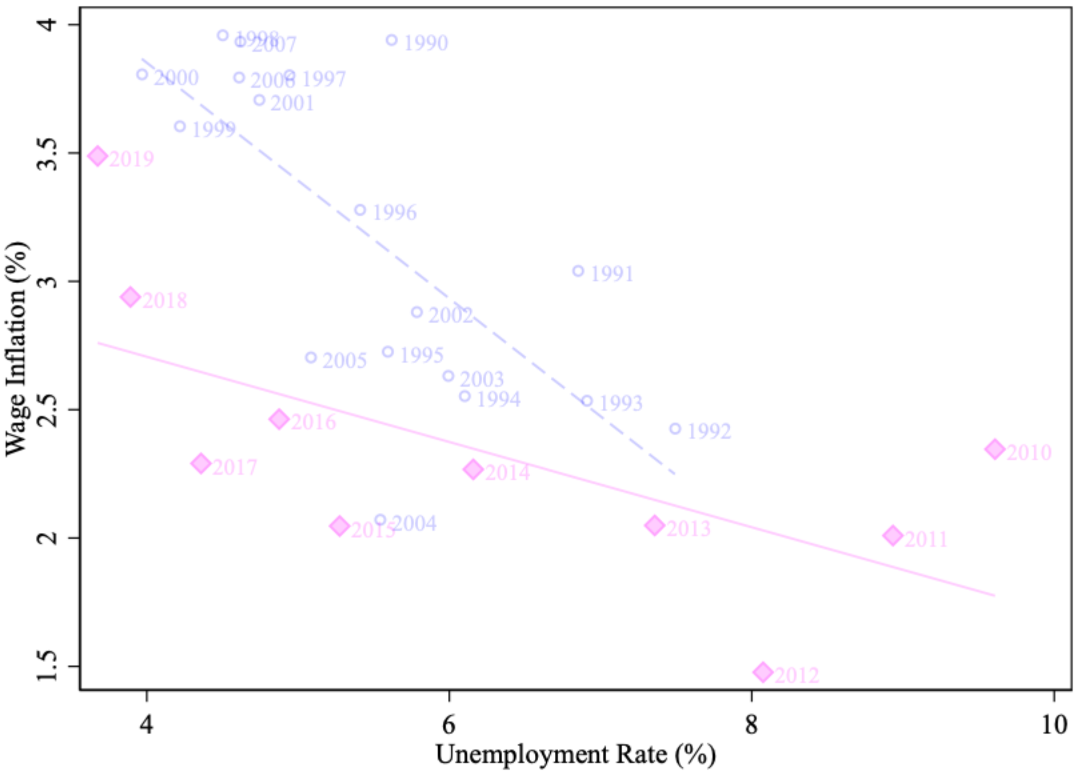
This table reports results for the following regression: Log Wage$_{i,c,t}$ $= \alpha + \beta_3$ MP shock$_t$ $\times$ Labor Market Power$_{i,c,t-1} + X_{i,c,t} + \gamma_{i,t} + \gamma_{c,t} + \varepsilon_{i,c,t}$, where Log Wage$_{i,c,t}$ is defined as the log wage of vacancies posted by firm i, in commuting zone c in quarter t. MP shock$_t$ is the monetary policy shock by Jarociński and Karadi (2020), in which a positive value reflects monetary policy tightening. Labor Market Power$_{i,c,t-1}$ is defined as the cumulative labor market share of firm i in commuting zone c at quarter $t-1$. For more details see section 3. Standard errors are double clustered at the firm and commuting zone level. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Wage Phillips Curve by Labor Market Power

	Wage Growth$_{c,t}$			
	(1)	(2)	(3)	(4)
Unemployment Rate$_{c,t}$	-1.546***	-1.735***	-2.745***	-5.301***
	(0.291)	(0.391)	(0.394)	(0.811)
$\mathbb{1}$ Labor Market Power$_{c,t}$	-0.090***	-0.091***	-0.078	-0.102**
	(0.031)	(0.031)	(0.052)	(0.050)
Unemployment Rate$_{c,t}$ $\times$ $\mathbb{1}$ Labor Market Power$_{c,t}$	1.840***	1.619***	2.810***	2.485***
	(0.529)	(0.529)	(0.747)	(0.728)
Obs.	6,333	6,333	6,333	6,333
Time FE		✓		✓
CZ FE			✓	✓

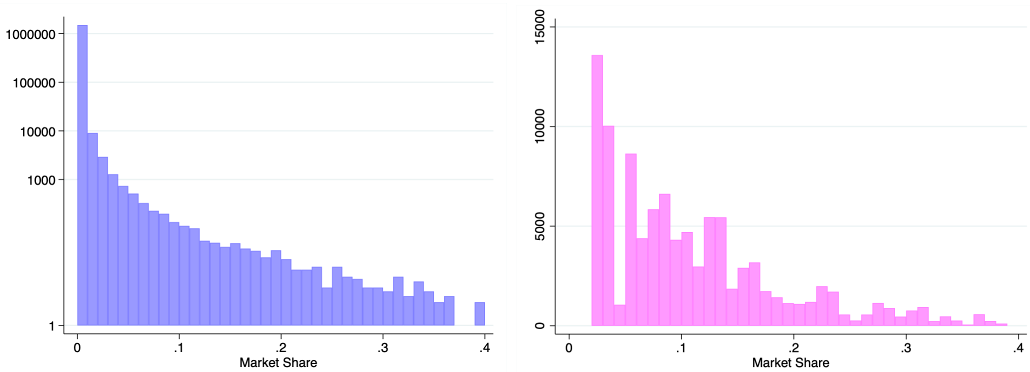
This table reports results for the following regression: Wage Growth$_{c,t}$ $= \alpha + \beta_1$ Unemployment Rate$_{c,t}$ $+ \beta_2\, \mathbb{1}$Labor Market Power$_{c,t} + \beta_3$Unemployment Rate$_{c,t} \times \mathbb{1}$Labor Market Power$_{c,t} + \epsilon_{c,t}$ where Wage Growth$_{c,t}$ is the annual wage growth of posted vacancies from Burning Glass Technology at the commuting zone-year level. $\mathbb{1}$Labor Market Power$_{c,t}$ is a dummy that is equal to one if the commuting zone has an HHI index based on vacancy postings above the median and zero otherwise. Unemployment Rate$_{c,t}$ is the unemployment rate from BLS at the commuting zone year-level. Standard errors are clustered at the commuting zone level. *** p<0.01, ** p<0.05, * p<0.1.

Figure 1: Wage Phillips Curve



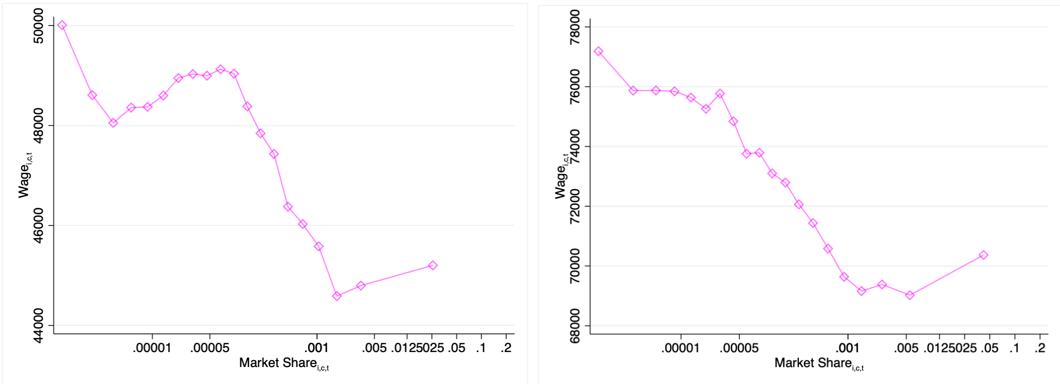
This figure plots wage growth against the unemployment rate. The pink diamonds ar for the years 2010-2019 und the pink solid line the linear fit. The blue hollow dots are for the years 1990-2007 and the blue dashed line the linear fit. The wage inflation is defined as the log change in average hourly earnings of production and nonsupervisory Employees, total private from the 'Current Employment Statistics (Establishment Survey)' following Galí and Gambetti (2019). The unemployment rate is from the U.S. Bureau of Labor Statistics.

Figure 2: Distribution of Labor Market Share



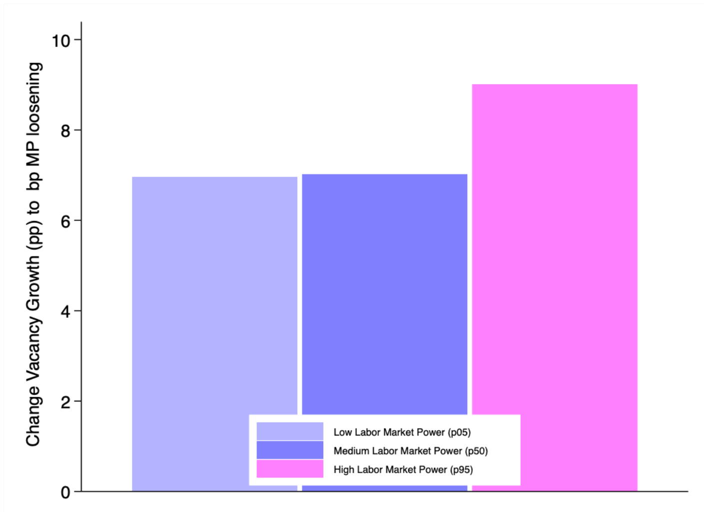
The left panel plots the histogram of the firm-commuting zone level market share defined as Market Share$_{i,c,t}$ = $\frac{\sum_{\tau \leq t} v_{i,c\tau}}{\sum_{\tau \leq t} \sum_i v_{i,c\tau}}$ for each firm i in commuting zone c in quarter t. Note that the frequency distribution is re-scaled to logs. The right panel plots the histogram of the 95th percentile of firm-level market share across commuting zones.

Figure 3: Labor Market Share and Wages



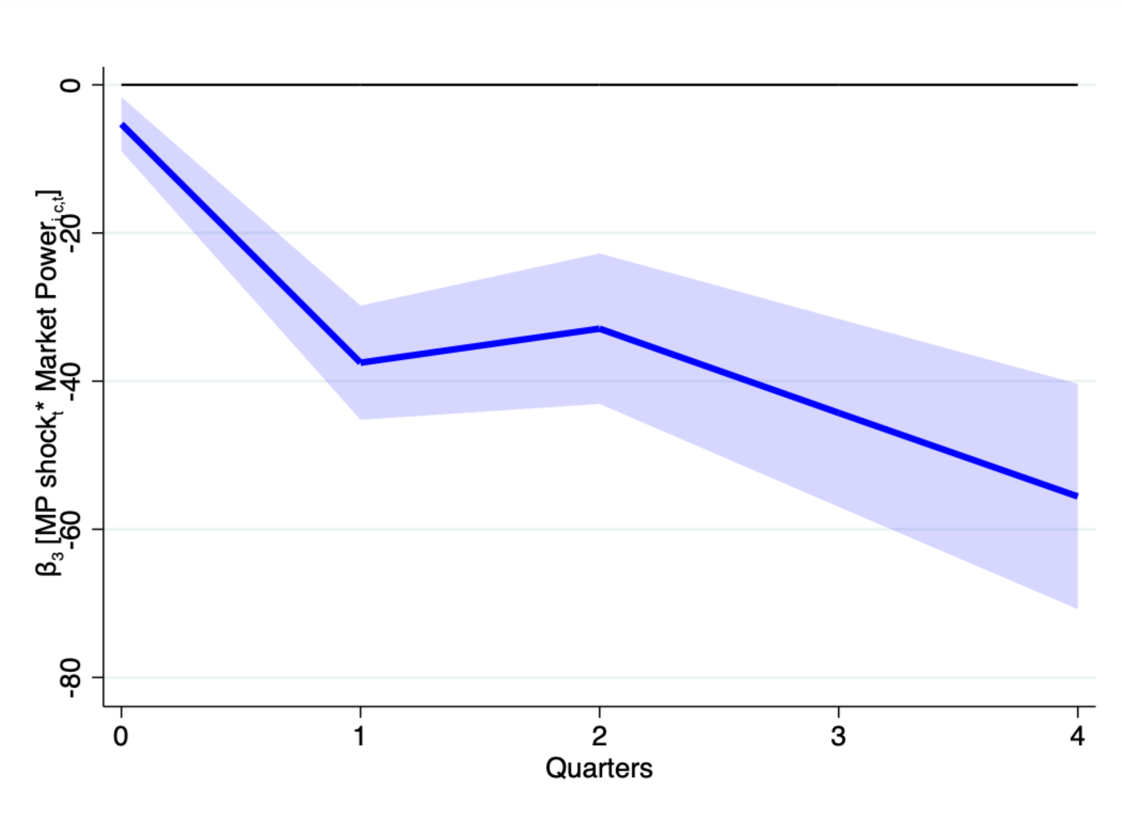
This figure plots a local polynomial smooth of wages on market share for non-college (left panel) and college (right panel) vacancies. The wages are defined as the average wage posted by firm i in commuting zone c in quarter t. The market share defined as Market Share$_{i,c,t} = \frac{\sum_{\tau \leq t} v_{i,c\tau}}{\sum_{\tau \leq t} \sum_i v_{i,c\tau}}$ for each firm i in commuting zone c in quarter t.

Figure 4: Change in Vacancy Postings in Response to Monetary Policy Accommodation



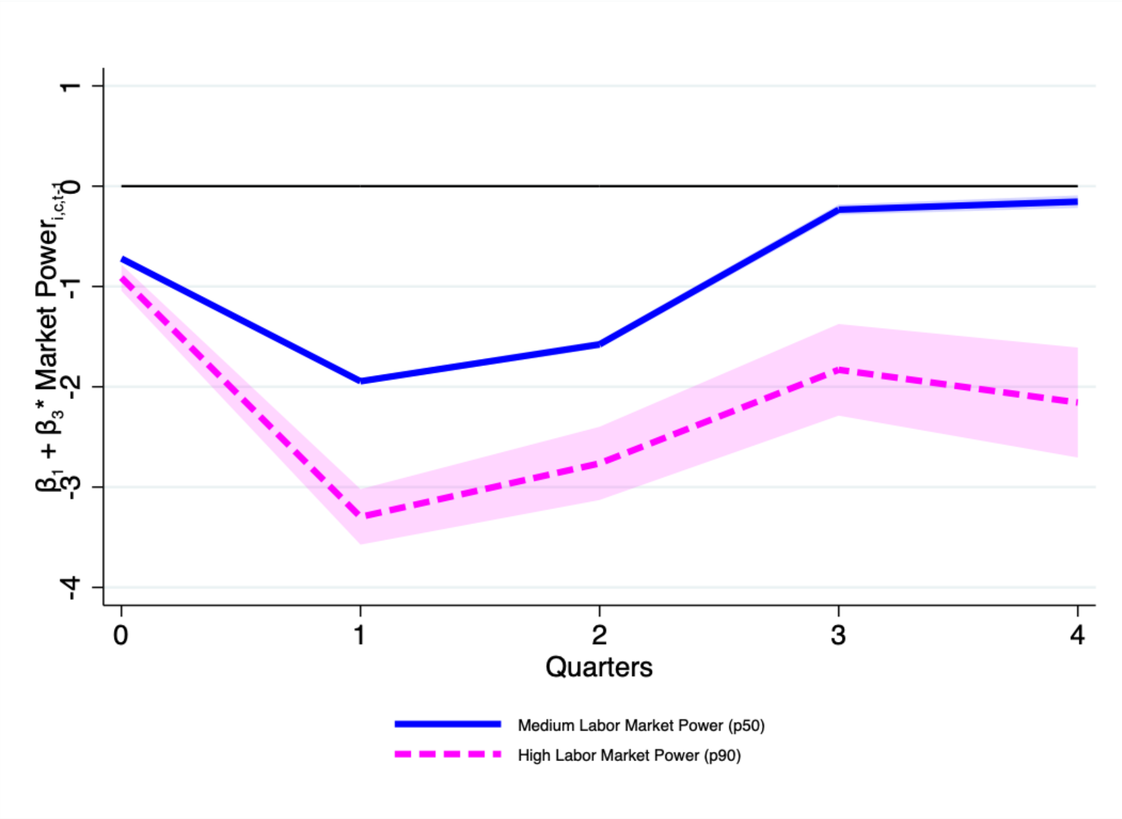
This figure plots the total effect of the accommodating monetary policy on vacancy postings given by: $\beta_{3,i}$ MP shock$_t \times$Labor Market Power$_{i,c,t-1}$. Labor Market Power$_{i,c,t-1}$ is defined as the cumulative labor market share of firm i in the commuting zone c at quarter $t-1$. For more details see section 3. The three bars represent the three levels of Labor Market Power - smallest (5th percentile of the distribution of the shares), medium (50th percentile of the distribution of the shares) and high (95th percentile).

Figure 5: Dynamic Labor Market Power Effect on Vacancy Postings in Response to Monetary Policy



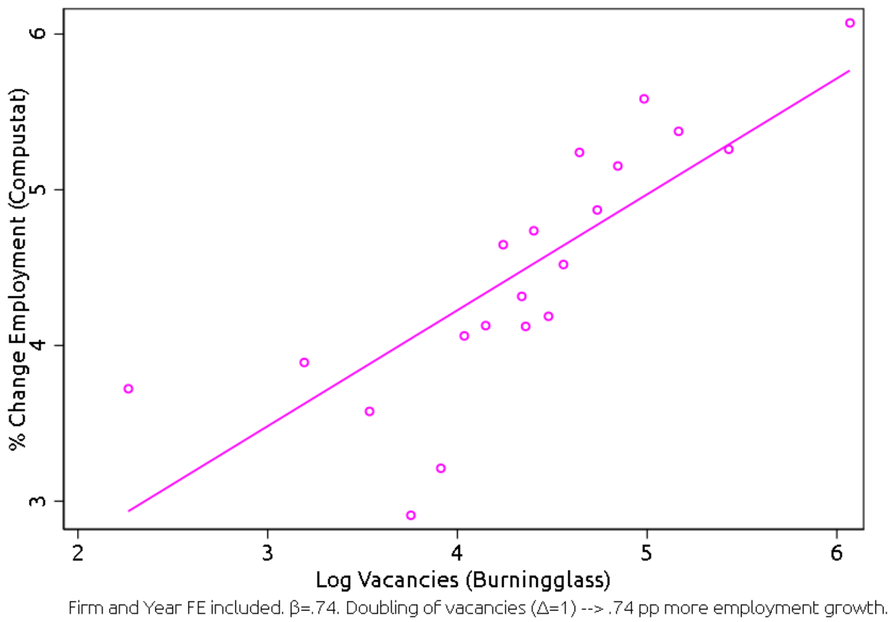
This figure plots β_3 of $\sum_{i=0}^{i=N}$ Log Vacancies$_{i,c,t+i} = \alpha + \beta_{3,i}$ MP shock$_t \times$ Labor Market Power$_{i,c,t-1} + X_{i,c,t} + \gamma_{i,t} + \gamma_{c,t} + \varepsilon_{i,c,t}$ where Log Vacancies$_{i,c,t}$ is defined as the log number of vacancies posted by firm i, in commuting zone c in quarter t. MP shock$_t$ is the monetary policy shock by Jarociński and Karadi (2020), in which a positive value reflects monetary policy tightening. Labor Market Power$_{i,c,t-1}$ is defined as the cumulative labor market share of firm i in commuting zone c at quarter $t-1$. For more details see section 3. Standard errors are double clustered at the firm and commuting zone level. *** p<0.01, ** p<0.05, * p<0.1.

Figure 6: Dynamic Response of Vacancy Postings to Monetary Policy



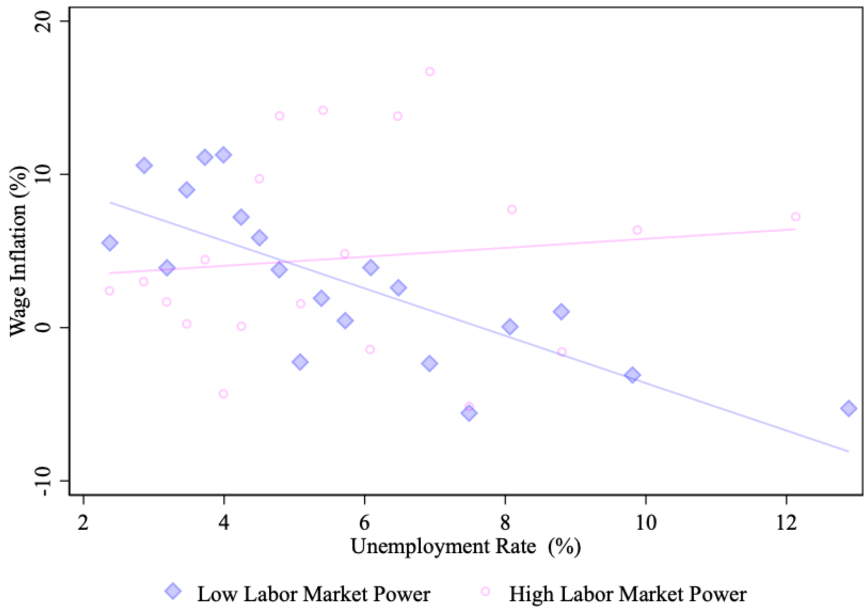
This figure plots the estimated response of vacancy postings for a firm a large extent of market power (95th percentile) in pink and medium market power (50th percentile) in blue from the following regression $\sum_{i=0}^{i=N}$ Log Vacancies$_{i,c,t+i} = \alpha + \beta_{1,i}$ MP shock$_t$ + $\beta_{3,i}$ MP shock$_t$ $\times$ Labor Market Power$_{i,c,t-1} + X_{i,c,t} + \gamma_i + \gamma_c + \varepsilon_{i,c,t}$ where Log Vacancies$_{i,c,t}$ is defined as the log number of vacancies posted by firm i, in commuting zone c in quarter t. MP shock$_t$ is the monetary policy shock by Jarociński and Karadi (2020), in which a positive value reflects monetary policy tightening. Labor Market Power$_{i,c,t-1}$ is defined as the cumulative labor market share of firm i in commuting zone c at quarter $t-1$. For more details see section 3. The pink lines is defined β_1 + β_3*Labor Market Power$_{i,c,t-1}(P95)$ and the blue line is defined as β_1 + β_3* Labor Market Power$_{i,c,t-1}(P50)$. Standard errors are double clustered at the firm and commuting zone level. *** p<0.01, ** p<0.05, * p<0.1.

Figure 7: Sensitivity of Employment to Vacancy Postings



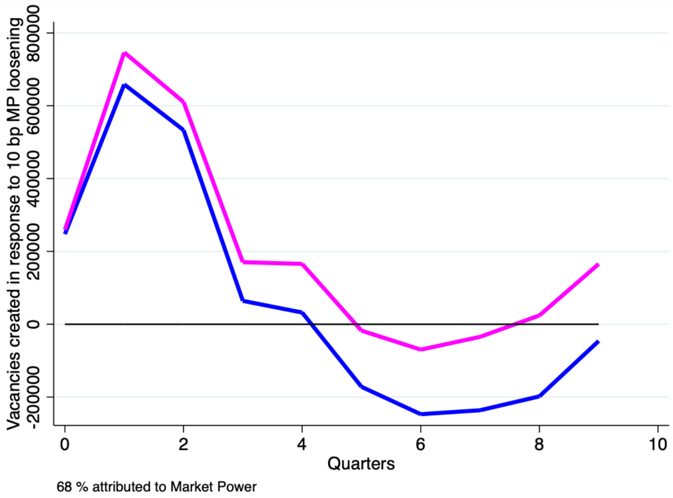
This figure plots a binscatterplot between the log change in employment from Compustat on Log Vacancy postings from BGT: $\Delta Employment_{i,t} = \alpha_i + \alpha_t + \beta_1 \text{Log Vacancies}_{i,t} + \epsilon_{i,t}$ where $\Delta Employment_{i,t}$ is the log change in employment of firm i between year t and $t-1$ in Compustat. Log Vacanciesi,t is the log number of vacancies posted by firm i in year t from BGT.

Figure 8: Wage Phllips Curve by Labor Market Power



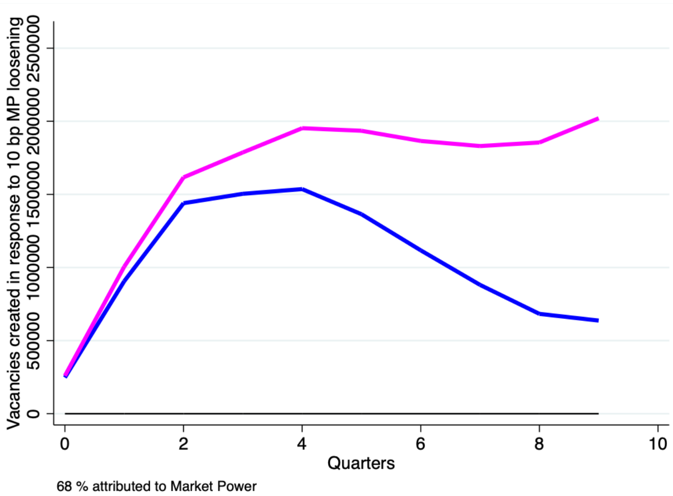
This figure plots a binscatter between wage growth and the unemployment rate on the commuting zone-year level. The y-axis refers to annual wage growth from Burning Glass Data vacancy postings. The x-axis measures the commuting zone unemployment rate based on BLS data. The blue (pink) diamonds (dots) reflect regions in which labor market power (as measured by the commuting zone year level HHI in vacancy postings) is below (above) the median.

Figure 9: Back-of-the-Envelope Calculation. Extra vacancies generated in the economies with and without labor market power



This figure plots the total number of vacancies generated in the economies with and without labor market power. The number of vacancies in the economy without labor market power is given by: $\sum_{i=0}^{i=N} \text{Vacancies}_i \times \beta_{3,i}$, effectively meaning that labor market power measures for each of the firms is equalized to zero. The number of vacancies in the economy with the actually observed levels of labor market power are given by: $\sum_{i=0}^{i=N} \text{Vacancies}_i \times [\beta_{3,i} + \beta_6 \text{Labor Market Power}_{i,c,t-1}]$, effectively using the actual levels of labor market power in the interaction term. Labor Market Power$_{i,c,t-1}$ is defined as the cumulative labor market share of firm i in the commuting zone c at quarter $t-1$. For more details see section 3. The response of the economy without market power is given in blue. The response of the economy with market power is given in magenta. The graphs show the additional vacancies generated in response to the monetary expansion in period zero for up to 9 periods ahead

Figure 10: Back-of-the-Envelope Calculation. Extra vacancies are generated in the economies with and without labor market power. Cumulative effect



This figure plots the cumulative number of vacancies generated in the economies with and without labor market power. The number of vacancies in the economy without labor market power is given by: $\sum_{t=0}^{t=\tau} \sum_{i=0}^{i=N} \text{Vacancies}_i \times \beta_{3,i}$, effectively meaning that labor market power measures for each of the firms is equalized to zero. The number of vacancies in the economy with the actually observed levels of labor market power are given by: $\sum_{t=0}^{t=\tau} \sum_{i=0}^{i=N} \text{Vacancies}_i \times [\beta_{3,i} + \beta_6 \text{Labor Market Power}_{i,c,t-1}]$, effectively using the actual levels of labor market power in the interaction term. Labor Market Power$_{i,c,t-1}$ is defined as the cumulative labor market share of firm i in the commuting zone c at quarter $t-1$. For more details see section 3. The response of the economy without market power is given in blue. The response of the economy with market power is given in magenta. The graphs show the cumulative additional vacancies generated in response to the monetary expansion in period zero for up to 9 periods ahead

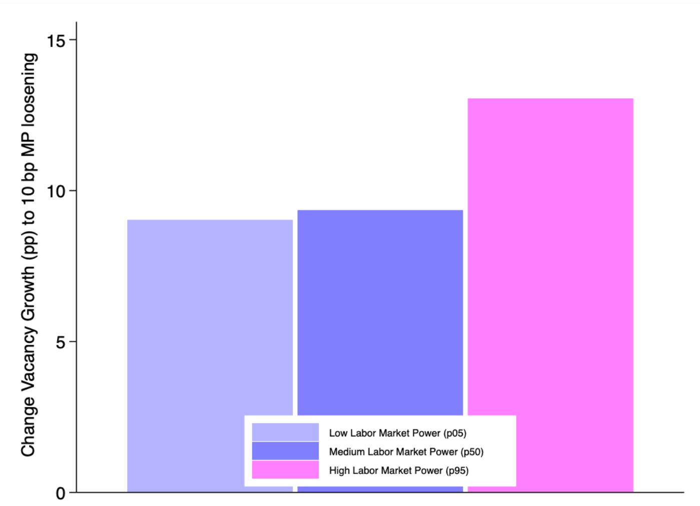
A Appendix Tables and Figures

Table A1: Labor Demand Effect of Monetary Policy

	Log Vacancies$_{i,c,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MP Shock$_t$	-0.456***	-0.830***		-0.903***			
	(0.010)	(0.010)		(0.010)			
Market Share$_{i,c,t-1}$	0.656***	-0.107***	-0.053***	0.967***	1.070***	1.206***	1.228***
	(0.007)	(0.008)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)
MP Shock$_t\times$ Market Share$_{i,c,t-1}$	-0.742***	-0.102***	-0.196***	-0.483***	-0.540***	-0.435***	-0.636***
	(0.039)	(0.034)	(0.033)	(0.034)	(0.033)	(0.049)	(0.057)
Obs.	8,614,533	8,559,755	8,559,755	8,559,755	8,559,755	7,170,733	7,170,364
Firm FE		✓	✓	✓	✓		
Time FE			✓		✓		
CZ FE				✓	✓	✓	
Firm*Time FE						✓	✓
CZ*Time FE							✓
No. Firms	307226	252448	252448	252448	252448	92179	92178

This table reports results for the following regression: Log Vacancies$_{i,c,t}$ $= \alpha + \beta_3$ MP shock$_t$ $\times$ Labor Market Power$^{alt}_{i,c,t-1} + X_{i,c,t} + \gamma_{i,t} + \gamma_{c,t} + \varepsilon_{i,c,t}$, where Log Vacancies$_{i,c,t}$ is defined as the log number of vacancies posted by firm i, in commuting zone c in quarter t. MP shock$_t$ is the monetary policy shock by Jarociński and Karadi (2020), in which a positive value reflects monetary policy tightening. Labor Market Power$^{alt}_{i,c,t-1}$ is defined as the cumulative labor market share of firm i in the corresponding industry in the commuting zone c at quarter $t-1$. For more details see section 3. $\gamma_{i,t}$ are firm-time, $\gamma_{c,t}$ are commuting-zone(CZ)-time fixed effects. Standard errors are double clustered at the firm and commuting zone level. *** p<0.01, ** p<0.05, * p<0.1.

Figure A1: Change in Vacancy Postings in Response to Monetary Policy Accommodation



This figure plots the total effect of the accommodating monetary policy on vacancy postings given by: $\beta_{3,i}$ MP shock$_t$ $\times$ Labor Market Power$^{alt}_{i,c,t-1}$. Labor Market Power$^{alt}_{i,c,t-1}$ is defined as the cumulative labor market share of firm i in the corresponding industry in the commuting zone c at quarter $t-1$. For more details see section 3. The three bars represent the three levels of Labor Market Power - smallest (5th percentile of the distribution of the shares), medium (50th percentile of the distribution of the shares) and high (95th percentile).

Table A2: Robustness to the Choise of Monetary Policy Shock

	Log Vacancies$_{i,c,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
MP shock$_{i,t}\times$ lag$_s firmcum$	-1.415***	-1.387***	0.693***	-2.942***	-0.849***	-1.430***
	(0.228)	(0.188)	(0.112)	(0.250)	(0.102)	(0.174)
R-squared	0.467	0.468	0.468	0.468	0.468	0.468
Obs.	12,851,727	12,851,727	12,851,727	12,851,727	12,851,727	12,851,727
Firm*Time FE	✓	✓	✓	✓	✓	✓
CZ*Time FE	✓	✓	✓	✓	✓	✓
No. Firms	NS	BRW	J u1	J u2	J u3	J u4

This table reports results for the following regression: Log Vacancies$_{i,c,t}$ $= \alpha + \beta_3$ MP shock$_t$ $\times$ Labor Market Power$^{alt}_{i,c,t-1} + X_{i,c,t} + \gamma_{i,t} + \gamma_{c,t} + \varepsilon_{i,c,t}$, where Log Vacancies$_{i,c,t}$ is defined as the log number of vacancies posted by firm i, in commuting zone c in quarter t. MP shock$_t$ are different monetary policy shocks, including NS Nakamura and Steinsson (2018), BRW Bu et al. (2021) and J u Jarocinski (2021), in which a positive value reflects monetary policy tightening. Labor Market Power$^{alt}_{i,c,t-1}$ is defined as the cumulative labor market share of firm i in the corresponding industry in the commuting zone c at quarter $t-1$. For more details see section 3. $\gamma_{i,t}$ are firm-time, $\gamma_{c,t}$ are commuting-zone(CZ)-time fixed effects. Standard errors are double clustered at the firm and commuting zone level. *** p<0.01, ** p<0.05, * p<0.1.