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Monetary Policy under Labor Market Power

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Monetary Policy under Labor Market Power

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ABSTRACT: Using the near universe of online vacancy postings in the U.S., we study the interaction between labor market power and monetary policy. We show empirically that labor market power amplifies the labor demand effects of monetary policy, while not disproportionately affecting wage growth. A search and matching model in which firms can attract workers by either offering higher wages or posting more vacancies can rationalize these findings. We also find that vacancy postings that do not require a college degree or technology skills are more responsive to monetary policy, especially when firms have labor market power. 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. In the current context of rising interest rates, unemployment is likely to rise more in poorer U.S. regions because labor market power is more prevalent there, thus leading to rising inequality.

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1 Introduction

In recent economic expansions, wages have grown slowly despite strong employment growth. For instance, the period following the global financial crisis (GFC)—a period of extremely accommodative monetary policy—was associated with a strong decline in the unemployment rate, especially among the less-skilled, while wages remained stagnant until very late in the expansion period. Such a flattening of the wage Phillips curve, see Galí and Gambetti (2019) and Figure 1, has led academics and central bankers to question the merit of relying on estimated deviations from the natural rate of unemployment to conduct monetary policy (Bernanke, 2022; Blanchard, 2018). 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, and on asymmetrically pursuing maximum employment (Powell et al., 2020).

In this paper, we argue that *labor market power* plays an important role in the transmission of monetary policy to labor demand and wage growth and can partially explain the flattening of the wage Philfips curve after the GFC. U.S. firms are well known to have significant labor market power, allowing them to "mark-down" wages from the marginal product of labor (Hershbein et al., 2022; Berger et al., 2022; CEA, 2022). Accommodative monetary policy raises the marginal product of labor, incentivizing all firms to hire more. However, since the wage elasticity of labor demand is lower for high labor market power firms, they can hire more workers without raising wages disproportionately. Consistent with this mechanism, we show empirically that accommodative monetary policy increases labor demand more for firms with labor market power, and that this comes without a disproportionate response in wages. In aggregate, this implies that due to the presence of labor market power, accommodative monetary policy can lead to a decline in the unemployment rate that is decoupled from an increase in wage growth. This channel can partly explain the flattening of the wage Phillips curve and the "wage-less" recovery after the Global Financial Crisis.

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. Vacancies are valued because workers value a higher probability of finding a job, beyond higher earnings when they are employed. 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. Throughout the paper, we relate vacancies to labor demand. BGT data cover 250 million online job vacancy postings that correlate strongly with firm-level changes in net employment. Details for each vacancy include information on the firm, location, posted date, job requirements, and offered wage, among others. The highly disaggregated data allow us to construct firm-region specific vacancy shares, which serve as our measure of labor market power. We combine these data with unexpected high-frequency monetary policy shocks around Federal Open Market Committee (FOMC) meetings.

Our measure of labor market power is connected to two theoretical approaches in the literature. Labor market power is a function of the share of total payroll of each firm in the Cournot competition model of Berger et al. (2022), in the spirit of Atkeson and Burstein (2008) for product market power. The share of vacancies of each firm is also a good approximation of labor market power in the search and matching model of Jarosch et al. (2019). This share 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 that are only available for publicly traded firms.

Our measure of labor market correlates with lower wages. We show that firms that have a larger vacancy share pay significantly lower wages even conditional on a large set of observed and unobserved firm, region and vacancy characteristics, such as the occupation and requirements for education, software, experience, among others. This negative correlation between vacancy share and wages provides assurance that the vacancy share indeed reflects market power (in the form of a markdown) and mitigates the concern that higher vacancy shares may reflect other factors.

We find that accommodative monetary policy significantly increases 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 with more labor market power, even after controlling for unobserved and observed time-varying regional and firm-time characteristics, ruling out many other potential channels unrelated to labor market power (such as financial constraints or product 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 economically large and statistically significant at least for eight quarters. A simple back-of-the-envelope calculation attributes to labor market power about one-quarter of the cumulative response of vacancies to monetary policy shocks after four quarters. This calculation compares the response of vacancies using the observed labor market power in the data to a scenario where we assume there is no labor market power.

Moreover, these effects of labor market power are more pronounced for vacancies with lower skill requirements. The labor demand effects of labor market power in response to monetary policy are even larger for vacancies that do not require a college degree or tech skills. On the other hand, the relative response of wages does not depend on the degree of labor market power. 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, implying a flattening of the wage Phillips curve (Figure 1).

To analyze the implications of labor market power for the wage Phillips curve directly, we estimate the wage Phillips curve on the commuting zone-level and exploit regional variation in the degree of labor market power. We find that the wage Phillips curve is steep for regions where labor market power is weak, while the relationship between wages and unemployment is economically and statistically insignificant for regions where labor market power is strong. These results suggest that monetary is substantially more effective in stimulating wage growth through reducing the unemployment rate in the presence of labor market power due to a flatter aggregate wage Phillips curve. This result is further confirmed when we analyze wage growth in regions with and without labor market power in response to monetary policy shocks. We find substantially weaker wage growth response in response to monetary policy accommodation in regions where labor market power is high.

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 make accommodative monetary policy less effective in generating employment, while at the same time, labor market power can dampen the effectiveness of loose monetary policy in stimulating wage growth, especially for the low-skilled. This suggests labor market power affects the inflation-unemployment sacrifice ratio.

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) find that firms that are less financially constrained tend to respond more to monetary policy shocks 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 concerns with monetary policy's distributional effects. Some papers emphasize the differential reaction of labor and capital income. For example, Andersen et al. (2021) find that while the reaction of labor income remains roughly the same for the top 50% of households, the reaction of capital income is considerably larger for the top 1%, up to twice as large as the reaction of labor income, resulting in disproportionate gains for this group from the monetary policy easing. Similarly, see De Giorgi and Gambetti (2017) for empirical evidence on the effects of technology shocks. Others, for instance, Dolado et al. (2021) draw a connection to the differential effects across categories of labor. The authors develop a model with capital-skill complementarity and show that in this model, wages of high-skilled workers are more responsive to monetary policy shocks, which means that a monetary policy easing increases 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 price 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 implications 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, particularly if thinking of tradable goods, while labor market power is regional due to the greater segmentation 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. Both 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,b,c, 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 Phillips curve after 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 coupled with an extended period of monetary loosening 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.

The remainder of 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 in response to monetary policy. Section 3 introduces our data, Section 4 discusses our measure of labor market power and presents stylized facts on labor market power, Section 5 details our empirical approach and results. Finally, Section 6 concludes.

2 Model

This section introduces a simple search and matching model and lays out conditions under which firms with labor market power adjust vacancies disproportionately in response to shocks, but not wages.

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. HH denotes a set of parameters coming from the household labor supply decision. 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 for 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 the 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.[1]

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

No assumptions are made about a firm's demand structure and we 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, labor, 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 having a higher likelihood of matching with workers. This could be due to a higher awareness of workers of these firms, i.e. due to higher visibility of their vacancies. Another alternative would be to consider the difference in costs for posting vacancies, with larger firms having lower costs. For now, we follow this second approach.

[1] This cost should not be interpreted merely as the actual cost of posting a vacancy, which is surely low. It includes the time of reviewing, interviewing, and selecting applicants which is typically very costly.

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

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

The first order conditions to this problem are:

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

where c is the marginal cost of posting a vacancy. As introduced above, MRL is the marginal revenue of labor and is given by the product of the marginal revenue and the marginal product of labor: $MRL = (py)'_l = MR \times MPL$. 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 is typical 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 that would prevail in competitive labor markets.

The novelty in this model is the first optimality condition that involves the trade-off between posting more vacancies and/or posting higher wages:

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

Recall that in this model, firms with higher market power are assumed to have lower vacancy posting costs. Because the hiring function is assumed to have 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 a positive 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 shock in this model can therefore be thought of as a shock to MRL since monetary policy shocks would combine a positive aggregate demand shock and the 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 monetary policy is assumed to not change households' 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.

The above equates labor market power with lower marginal costs of hiring. Other papers model instead the impact of labor market power on the elasticity of labor supply. In the search and matching framework developed by Jarosch et al. (2019), the fact that a firm accounts for a larger share of vacancies increases the probability of a single worker coming across that firm in the future. This gives the firms with larger shares more control over workers' outside options and allows for a stronger bargaining position, which results in lower wages. We intend to extend our model to incorporate such considerations in future versions of this paper.

We now turn to the empirical analysis to examine whether the predictions of our model are borne out in the data.

3 Data

3.1 Burning Glass Technologies (BGT)

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 $\approx$ 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 a more 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 postings include the exact date when the vacancy was 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 representation of local labor markets.

BGT data also offers other significant details on the type of vacancy. NAICS industry and ONET occupation breakdowns are available. A large proportion of vacancies also lists job requirements, such as education or software 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 some shortcomings due to 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 over-representation 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. Hazell et al. (2021) find that 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, they find that smaller firms and occupations with lower skill requirements are more likely to report wages in Burning Glass. Some postings list a wage range — in these instances, we take the midpoint of that range. For most of our analysis, we collapse vacancy-level data into a panel of firm-, commuting zone- and quarter-level, or effectively an establishment-level panel. Wage data on annual compensation and does not include bonuses and other benefits beyond the basic wage.

Our unit of analysis is the firm-commuting zone-time level. We have in total over 15 million firm-commuting zone-quarter observations with a total of over 380,000 firms and just over 700 commuting zones. The average commuting zone has postings from 22,000 firms, although this is unevenly distributed. An average firm posts in 170 commuting zones (see Table 1 for further details).

3.2 Monetary Policy shocks

The baseline measure of monetary policy shocks we use is that developed in Jarociński and Karadi (2020) — JK 2020 henceforth. 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 in 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 after the following policy meeting, not the immediate next meeting. These shocks do not capture surprises to the balance sheet, implicitly assuming that such changes are orthogonal to surprises to the policy rate (and that balance sheet measures would not affect the 3-month futures).

We prefer JK 2020 shocks because they separate pure monetary policy shocks from signaling shocks related to the state of the economy — so called "Fed information" shocks. The latter capture the fact that economic agents take Fed actions as a signal about the state of the economy and adjust their expectations accordingly. For instance, a surprising monetary loosening 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 shocks, therefore, goes in the opposite direction to that of monetary policy, and mixing the two together can significantly bias the results and confound channels. As a baseline, we are only interested in the effect of the monetary policy shock and we use the Fed information shock as a control.

As a robustness check, we also 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 in one shock surprises across the yield curve from one-month to two-year. Jarocinski (2021) estimates four different shocks, including the standard monetary policy shock and three orthogonal shocks that do not affect near-term fed funds futures. The other shocks include: (i) an Odyssean forward guidance shock (a commitment to a future course of policy rates); (ii) a shock to longer-term treasury yields mostly affected by asset purchase announcements; and (iii) 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.

Figure A1 presents the time-series of JK 2020 shocks, both monetary policy and central bank information. Monetary policy shocks exhibit both significant tightening and loosening. Our vacancy dataset includes years 2007 and 2010-2019. Over this period, the largest tightening and loosening shocks happened in 2007. The global financial crisis-related loosening cycle started in August 2007 and in the run up to it uncertainty over the state of the economy and thus over monetary policy was elevated.

3.3 Compustat

We merge BGT and Compustat data for a large number of publicly traded firms to analyze the relationship between vacancy postings and employment growth. We aggregate vacancy postings to the firm level and fuzzy merge the BGT firm name to Compustat. First, we execute a standard string cleaning procedure, removing excessive spacing, acronyms related to a companys business structure acronyms, special characters, and other unnecessary characters from the name. Given the string differences between the names of companies in BGT and Compustat, we used a two-layered merging technique consisting of exact matching, and Jaro-Winkler string distance matching (Jaro, 1989; Winkler, 1990). For the Jaro-Winkler fuzzy matching, we set a string distance threshold of 0.11, which maximizes the number of matches and their quality jointly. We obtain 8,231 firm matches from 14,983 firms in Compustat in the years between 2008 to 2019, of which 3,217 are exact matches, and 5,014 match using the Jaro-Winkler fuzzy matching. The merged companies represent 75% of sales, and 73% of employment of all companies in Compustat.

We follow the cleaning procedure of Ottonello and Winberry (2020) for the Compustat data closely. First, we keep only corporations incorporated in the US. In particular, we drop firms in the financial and utilities sectors, firm-quarter observations with acquisitions larger than 5 percent of assets, firm-quarter observations where the investment rate is in the top and bottom 1 percent of the distribution, the investment spell is shorter than 40 quarters, firm–quarter observations where liquidity, debt, and sales are outliers, firms with less than 10 million US dollars in assets, and that are in the sample less than 5 years. Since the quarterly version of Compustat does not have employment information, we linearly interpolate the annual employment data to quarterly data.

4 Measuring Labor Market Power in BGT

4.1 Definition of Labor Market Power (LMP)

In our baseline, we measure labor market power with the share of vacancies posted by a single firm in a local labor market out of the total vacancies posted in that labor market.[2] We define a local labor market as a U.S. census commuting zone. This fine breakdown implies that some smaller firms do not post vacancies in two consecutive periods. To avoid losing too many observations, we use the cumulative vacancies up to any given date to compute vacancy shares in the following way:

$$\text{Labor Market Power}_{i,c,t} = \text{Vacancy Share}_{i,c,t} = \frac{\sum_{\tau \leq t} v_{i,c,\tau}}{\sum_{\tau \leq t} \sum_{i} v_{i,c,\tau}} \tag{2}$$

where vacancies in commuting zone c, for firm i at time τ are denoted by $v_{c,i,\tau}$. An additional advantage of using this cumulated vacancy share is that it might correspond more closely to employment shares rather than vacancy shares and it is also less endogenous to the particular period of the shock and outcome.

When we refer to "high labor market power firms" or "a firm with labor market power", we use the 95th percentile across the full distribution of firm-CZ-time observations as a cutoff. Vacancy shares are highly skewed, with most firms commanding close to zero shares and a small number of firms having substantial labor market power. Figure 2 plots the histogram of labor market power as measured in Equation 2. The left-hand side plots the distribution of vacancy shares across firms at the commuting zone level. The right-hand side plots the distribution of vacancy shares across commuting zones for firms with labor market power only (those with vacancy shares greater than the 95th percentile, as defined just above). The average vacancy share is 0.8%, the median is 0.1%, and the 95th percentile is 3.7%.

Theoretically, higher labor market power should correspond to lower wages in the cross-section. Figure 3 plots firms' commuting zone-level average posted wage on the y-axis against the vacancy share of that same firm in the same commuting zone on the x-axis. To account for the right-skewed nature of vacancy shares, the x-axis uses a log-scale. The left panel plots the relationship for non-college vacancies and the right panel for college vacancies. A large portion of the distribution of vacancy shares offers similar posted wages. In particular, firms with a vacancy share between 0 and 0.00005 (0.005 percentage points) post an average wage between US$50,000 and US$48,000 for non-college vacancies. These firms have extremely low labor market power, and within that

[2]Using a firm's share of vacancies as a proxy for market power is related to two strands of the literature: in oligopsonistic settings, see Berger et al. (2022), or in search and matching models, seeJarosch et al. (2019).

group differences are not meaningful. A firm that accounts for a vacancy share of 0.00005 posts 1 out of 20,000 vacancies. However, once a firm starts to control more than 0.005 percentage points of the market their posted wage declines strongly. For instance, a firm with a vacancy 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, with posted wages declining more linearly than for non-college vacancies, but with a large drop in posted wages at vacancy shares of about 0.005%. As expected, the overall level of wages posted is significantly higher at around US$76,000 for firms with a vacancy share of < 0.00005) and around US$70,000 for firms with a vacancy share of > 0.001.

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

To exclude other drivers of wages, we estimate vacancy-level regressions in which we control for a large set of vacancy characteristics and find that even after controlling for observed and unobserved vacancy, firm, and region characteristics, firms with higher vacancy shares post lower wages on their vacancies (Table 2). We interpret this evidence that the vacancy share is a good proxy for actual labor market power.

Alternative Definitions of LMP

In the literature, labor markets are sometimes not defined at the commuting zone-level, but rather at a finer level with an additional industry breakdown. We check robustness of our results to this alternative definition and find similar results (see discussion in section 5).

We also compute the Herfindahl-Hirschman index (HHI) of vacancy postings at the commuting zone level as another alternative measure of labor market power. Such a measure is commonly used in the literature to assess the competitiveness of a particular market. HHI is given by:

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

where the vacancy share is calculated following Equation 2. We use HHI to assess whether commuting zones where firms have more market power have flatter Phillips curve.

4.2 Stylized Facts on LMP

In this subsection we document the location of firms with significant labor market power and the sectors they operate in. For instance, we explore whether they are highly productive "superstar" firms, or firms that dominate smaller local labor markets. We find the latter is true.

To tackle these questions, we examine the characteristics of regions that host firms with high labor market power. Regions where firms with labor market power are present tend to have lower GDP per capita, lower house prices, a smaller labor force, and looser labor markets (see Table 3). They also, as expected, exhibit a higher HHI. Those findings seem to indicate that we are more likely to find higher labor market power firms in less advantaged regions. This also becomes apparent when we plot labor market power on a map of the U.S. (Figure 4). Note that regions with firms with high labor market power are consistently in the middle of the country, and are notably absent in the coasts or around larger cities.

Second, we investigate labor market power from the sectoral and firm perspectives. The sectors where firms with high market power are prevalent include health care, educational services, agriculture, public administration, retail trade and mining (Figure 5). Interestingly, high labor market power firms are more likely to be in tradable sectors.[3]

5 Empirical results

This section documents that firms with labor market power raise vacancies by more following a monetary policy shock, without having to increase wages by more compared to firms without labor market power. Moreover, these effects are highly heterogeneous 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. Throughout the discussion we focus on monetary policy easing shocks and thus a positive coefficient involving monetary policy means the variable rises with monetary policy easing.

5.1 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:

$$\text{Log Vacancies}_{i,c,t} = \alpha + \beta \text{ MP easing}_t \times \text{LMP}_{i,c,t-1} + \theta X_{i,c,t} + \gamma_{i,t} + \gamma_{c,t} + \varepsilon_{i,c,t} \quad (3)$$

[3] 47% of high LMP firms are in tradable sectors versus 36% of low LMP firms.

where LMP denotes labor market power as measured by the vacancy share defined in Equation 2, $X_{i,c,t}$ includes the Federal Reserve information shock and its interactions with vacancy 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.

Vacancies of firms with labor market power are more responsive to monetary policy shocks (see Table 4). As we move from column 1 to column 7, a more extensive set of fixed effects are included in the regressions. Column 1 shows the results of Equation 3 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 positive and statistically significant. The coefficient of 0.348 indicates that for a firm without labor market power, vacancy postings rise by 3.48% in response to a 10 basis points expansionary monetary policy shock. The interaction between the monetary policy shock and lagged vacancy share is also positive and statistically significant. This means that labor market power amplifies the response of monetary policy shocks, i.e. firms that have a larger vacancy share in a commuting zone raise their vacancy postings by even more compared to a firm that has no labor market power in response to a monetary policy easing shock. In column 2 we include firm fixed effects to control for unobserved and observed time-invariant heterogeneity at the firm-level, for instance, the average number of vacancies a firm posted 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 drops the coefficient on the monetary policy shock itself as that is collinear with the time fixed effect. Hence, we can only interpret the differential impact with respect to labor market power and not the total response of vacancies to monetary policy. Still, as in columns 2 and 3, the interaction term is positive and statistically significant. Column 4 introduces commuting zone fixed effects relative to column 2. The inclusion of the regional effects controls for potential time-invariant confounding factors at the regional level, such as average income per capita during our sample period. The inclusion of commuting fixed effects leaves the results unchanged, as does the simultaneous inclusion of firm, time, and commuting zone fixed effects done in column 5.

The introduction of firm-time fixed effects in column 6 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. Firm-time fixed effects control 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 and thus results in 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 from 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.[4] Instead, since labor markets are more local, 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*.

Column 7 denotes our preferred baseline specification using commuting-zone-time fixed effects in addition to firm-time fixed effects. Commuting-zone-time fixed effects control, for example, for region-specific time-varying characteristics such as the concentration of vacancies. The specification in column 7 thus tests whether, conditional on the tightness of the regional labor market, firms with more market power respond differentially to monetary policy. As in specifications without the inclusion of as extensive fixed effects, firms with more labor market power adjust their labor demand more compared to other firms. Quantitatively, the interaction term between the monetary policy shock and the local vacancy share is -7.895 and varies little relative to the other specifications (other than that in column 1). The coefficient can be interpreted as follows: for a firm that controls 10% of the local labor market (slightly less then the 99th percentile of the $LMP_{c,t}$ distribution), 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. While this number may seem large, a 10% vacancy share is very rare.

The results are also illustrated in Figure 6 with numerical examples. We use column 4 of Table 4 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 vacancy 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

[4] 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.

column 4 of Table 4. 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.

The results in Table 4 are qualitatively robust to using different definitions of monetary policy, see Table A1. Similarly, using an alternative definition of labor market power that uses the cumulative share of vacancies of a given firm within the industry and local labor market it operates rather than just within its local labor market does not change the overall results (see Table A2 and Figure A2). Moreover, the results are robust to excluding the public administration sector (Table A3).

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

We estimate the following equations:

$$\sum_{h=0}^{H} \text{Log Vacancies}_{i,c,t+h} = \alpha_H + \beta_H \text{ MP easing}_t \times \text{LMP}_{i,c,t-1} + \theta_H X_{i,c,t} + \gamma_{i,t+H} + \gamma_{c,t+H} + \varepsilon_{i,c,t+H}$$

where H is a given quarterly horizon.[5] Figure 7 plots the estimated response of vacancy postings for a hypothetical firm with 100% labor market across different horizons. The response of vacancies to a monetary policy shock of firms with labor market power is persistently different and increases over time compared to those that do not have labor market power.[6] Figure 8 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. Within the first two quarters, firms with a large degree of labor market power increase their labor demand by around 3% in response to a 10 basis point monetary policy loosening, while those with median labor market power raise their demand by only 2%. However, for the firm with median labor market power, the effect of monetary policy seems to wear off over time, with the additional number of

[5] If BGT data does not report a vacancy for a given firm in a given commuting zone and quarter we assume there were no vacancy postings for these regressions.

[6] Point estimates and standard errors can be gleaned from Table A5.

vacancy postings cut in half after six quarters. In contrast, firms with significant labor market power seem to retain almost unchanged their initial response even after 6 quarters, suggesting that monetary policy shocks have much more persistent effects for firms with labor market power.

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 BGT data 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:

$$\begin{aligned}\text{Log Vacancies}_{i,c,t,j} = \alpha + &\beta \text{ MP easing}_t \times \text{LMP}_{i,c,t-1} + \\ &\gamma \text{MP easing}_t \times \text{LMP}_{i,c,t-1} \times \text{Type}_j + X_{i,c,t} \\ &+ \gamma_{i,t} + \gamma_{c,t} + \varepsilon_{i,c,t}\end{aligned} \tag{4}$$

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 γ captures whether there is significant heterogeneity across a particular type of vacancy. If the double interaction (β) has a different sign than the triple interaction (γ), that would mean that the effect is weaker for [Type = 1].

Table 6 shows estimates of Equation 4. 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, vacancy 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 although weaker 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.

Looking at the full dynamics of effects over vacancy types, we find that the effect of labor market power for vacancies not requiring college only grows over time and that of vacancies requiring software skills also becomes stronger (see Figure 9 and Table 7).

Figure 10 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) separating the responses of college (left) and non-college vacancies (right). In the case of non-college vacancies, the response of vacancies to a monetary policy shock of firms with labor market power is persistently different and increases over time compared to those that do not have labor market power. For college vacancies there isn't a meaningful difference beyond the first quarter.

Our specification is based on symmetric effects of positive and negative monetary policy surprises.[7] Following a contractionary (expansionary) surprise shock, firms with labor market power cut (expand) their vacancies by more than firms without labor market power, although the effect of the monetary policy shock on wages is similar across firms with and without labor market power. However, there are important compositional effects. Following a contractionary (expansionary) shock, the share of vacancies by high market power firms decreases (increases) and since these firms pay lower wages on average and have a higher markdown, this dampens the effect of the monetary policy shock on aggregate wages.

5.2 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 are not publicly available.

[7] We check for asymmetries in the effects but found no significant evidence of differential effects of positive and negative surprise shocks. Results are available from the authors upon request

To understand the relationship between vacancy postings and employment, we estimate the following regression equation:

$$\Delta Employment_{i,t} = \alpha_i + \alpha_t + \beta_1 \text{Log Vacancies}_{i,t} + \epsilon_{i,t} \tag{5}$$

where $\Delta Employment_{i,t}$ is the log change in employment of firm i between year t and $t-1$ in Compustat.[8] 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 5.1, 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 5. Figure 11 shows the result of Equation 5 in a scatterplot. The relationship between the 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 8 had shown that after four quarters, a firm with high labor market power increased its vacancy postings by a factor of 2 in response to a 10 basis point accommodative monetary policy shock. A firm with medium labor market power instead did not increase its 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 calculation makes several 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

[8] The contemporaneous specification reflects the fact that most vacancies are filled well before a year passes, for instance, the average time to fill a vacancy stayed at approximately one month in the time period we consider per Job Openings and Labor Turnover Survey (JOLTS).

there is a strong relationship between vacancy postings and employment growth [9]

To further verify the results hold for employment rather than vacancies, we estimate the dynamic response of employment in Compustat.

We estimate the following regression:

$$\sum_{h=0}^{H} \Delta \text{Employment}_{i,t+h} = \alpha_H + \beta_H \text{ MP easing}_t \times \text{LMP}_{i,t-1} + \theta_H X_{i,t} + \gamma_i + \gamma_{t+H} + \varepsilon_{i,t+H}$$

where $\Delta\text{Employment}_{i,t+h}$ is defined as the log difference between employment in time t+h and t-1. MP easing_t is the negative of the monetary policy shock by Jarociński and Karadi (2020), in which a positive value reflects monetary policy easing. $\text{LMP}_{i,t-1}$ is defined as one if the firm is in the top 5% of labor market power in at least one commuting zone. Standard errors are clustered at the firm level. Shaded areas represent a 95% confidence interval.

Figure 12 plots β_h of this regression. In response to a 10 bp monetary easing shock firms with labor market power increase their employment by 1-2 percentage point more than firms without labor market power within the first year. The result is consistent with the above back-of-the-envelope calculation, under which the response is around 1.5%.

5.3 Monetary Policy, Labor Market Power and Wages

We run the same specification as equation (3) substituting the dependent variable for posted wages measured as deviations from the regional average posted wage.[10] The resulting wage measure is given by:

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

We then estimate the following local projections:

$$\sum_{h=0}^{H} \text{Posted Wage}_{i,c,t+h}/H = \alpha_H + \beta_H \text{ MP easing}_t \times \text{LMP}_{i,c,t-1} + \theta_H X_{i,c,t} + \gamma_{i,t+H} + \gamma_{c,t+H} + \varepsilon_{i,c,t+H}$$

We note that BGT data for posted 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

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

[10]Average regional wages are subtracted to abstract from compositional effects, for example after a contractionary shock postings in high wage regions (low LMP) fall by less biasing the response of wages up. This is allowing to partial out commuting zone time characteristics.

a range is reported we take the average between the min and the max.[11] Table 8 and Table 9 show that an accommodative monetary policy shock increases posted wages, as expected, particularly in the short term (see also Figure 13). However, the response of posted wages to the monetary policy shock is not significantly different for firms with or without labor market power, including across horizons as can be observed in Figure A4 (since we do not condition on vacancies, this means that firms with more labor market power increase vacancies by more and increase employment by more without having to post higher wages).

5.4 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 5.2) for firms with labor market power, but the absent effect of labor market power on monetary policy shock transmission to 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. As shown in the introduction, the wage Phillips curve has flattened significantly and was particularly flat during the period between the GFC and the Covid-19 crisis (see Figure 1). 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 data from BLS, we estimate the following regression equation:

$$\begin{aligned} \text{Wage Growth}_{c,t} = \alpha + \beta_1 \text{ Unemployment Rate}_{c,t} + \beta_2 \, \mathbb{1}\text{LMP}_{c,t} + \\ \beta \text{Unemployment Rate}_{c,t} \times \mathbb{1}\text{LMP}_{c,t} + \epsilon_{c,t} \end{aligned} \tag{6}$$

where Wage $\text{Growth}_{c,t}$ is the annual wage growth of posted vacancies from Burning Glass Technology at the commuting zone-year level. 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, $\mathbb{1}\text{LMP}_{c,t}$, 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.

[11] Hazell et al. (2021) suggests that employers pay the posted wages, and that smaller firms tend to post wages.

(2020). Unemployment $\text{Rate}_{c,t}$ is the unemployment rate from BLS at the commuting zone year-level.

Figure 14 shows the commuting zone-level wage Phillips curve graphically in the form of a binscatter based on the regression Equation 6. 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 10, where we show the regression Equation 6 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. 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 when there is high labor market power.

Overall, this result suggests that labor market power flattens the wage Phillips curve and serves as an explanation for 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.

6 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 explored whether labor market power changes the transmission of monetary policy to labor market outcomes. 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 high labor market power in a certain region expands its vacancy postings by about 30% more relative to its counterparts. Moreover, the effect on vacancies is much more persistent for those with high labor market power. In contrast, labor market power does not significantly amplify the effects of monetary policy shocks on wages.

We detect significant heterogeneity across vacancy types. Vacancies that require a college degree and those requiring "tech-skills" are far less responsive to monetary policy than those that do not require a college degree and are targeted towards non-tech workers. Monetary policy cycles can thus generate significant heterogeneity in labor demand across the skill distribution, something that is consistent with recent data on the polarization of the labor market.

Our results can partly explain why before the Covid-19 crisis the unemployment rate declined significantly, but wages lagged behind. Our empirical results are corroborated by a search and matching model that predicts that firms with labor market power can hire more workers by posting more vacancies without increasing the wage, if they benefit from more efficient job matching or lower costs of posting vacancies. 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.

These findings have important implications for the conduct of monetary policy. In the presence of elevated labor market power, monetary policy is able to stimulate employment without materially driving wages and hence prices up, i.e. labor market power may increase the sacrifice ratio between inflation and unemployment. While this may seem beneficial, it also means that when inflation is very low, monetary policy has a very difficult time engineering a reflation. On the other side of the coin, a high sacrifice ratio is clearly a challenge when there is a need to disinflate. The presence of high labor market power means that unemployment will need to rise more than it would otherwise.

Going forward, the ongoing monetary policy tightening will likely hurt labor demand more in regions 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 reducing the number of employees rather than through lowering wages. This could potentially diminish the wage-price pass-through of monetary policy.

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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 total number of observations and the number of observations across the time and geographical dimensions of the data

Table 2: Relationship Between Wages and Our Measure of Labor Market Power At the Vacancy-Level

	Log wage$_{v,i,c,t}$				
	(1)	(2)	(3)	(4)	(5)
LMP$_{i,c,t}$	-0.360***	-0.193**	-0.168***	-0.174**	-0.181***
	(-3.85)	(-2.44)	(-2.83)	(-2.31)	(-2.81)
College$_{v,i,c,t}$	0.238***	0.236***	0.173***	0.170***	0.162***
	(41.46)	(31.56)	(36.31)	(37.33)	(40.28)
Software Skills$_{v,i,c,t}$	0.028***	0.028***	0.015***	0.015***	0.013***
	(8.13)	(7.01)	(4.25)	(4.34)	(4.51)
Specialized$_{v,i,c,t}$	0.088***	0.077***	0.056***	0.057***	0.054***
	(29.65)	(23.80)	(21.47)	(23.04)	(24.33)
Routine Manual$_{v,i,c,t}$	-0.110***	-0.105***	0.037***	0.037***	0.049***
	(-18.83)	(-15.99)	(3.36)	(3.44)	(4.50)
Routine Cognitive$_{v,i,c,t}$	-0.144***	-0.132***	0.054***	0.056***	0.071***
	(-28.15)	(-22.18)	(5.16)	(5.72)	(7.01)
Non-Routine Manual Physical$_{v,i,c,t}$	-0.058***	-0.057***	0.036***	0.040***	0.033***
	(-9.42)	(-8.36)	(3.18)	(3.60)	(3.51)
Non-Routine Manual Inter-Personal$_{v,i,c,t}$	0.044***	0.044***	0.038***	0.037***	0.042***
	(10.32)	(9.31)	(3.87)	(3.89)	(3.99)
Non-Routine Cognitive Analytical$_{v,i,c,t}$	0.064***	0.057***	0.103***	0.106***	0.102***
	(12.20)	(9.83)	(12.89)	(13.88)	(12.66)
Non-Routine Cognitive Personal$_{v,i,c,t}$	0.159***	0.158***	0.040***	0.041***	0.040***
	(33.75)	(28.52)	(7.02)	(7.73)	(8.10)
Obs.	12,714,694	12,356,399	11,862,438	11,857,790	11,857,284
Firm FE	✓				
Firm × Time FE		✓	✓	✓	✓
CZ × Time FE	✓	✓	✓	✓	✓
Industry × Time FE	✓	✓	✓	✓	✓
ONET × Time FE			✓	✓	✓
ONET × CZ FE				✓	✓
ONET × Industry FE					✓
No. Firms	173,057	144,813	141,764	141,715	141,708

This table reports results for the following vacancy-level regression: Log wage$_{v,i,c,t} = \alpha + \beta$ LMP$_{i,c,t} + \theta X_{v,i,c,t} + \gamma_{i,t} + \gamma_{c,t} + \gamma_{ind,t} + \gamma_{occ,t} + \gamma_{occ,c} + \gamma_{occ,ind} + \varepsilon_{v,i,c,t}$, where Log wages$_{v,i,c,t}$ is defined as the log of posted wage in vacancy v for firm i, in commuting zone c in quarter t. LMP$_{i,c,t}$ is defined as the cumulative vacancy share of firm i in commuting zone c at quarter t. $X_{v,i,ct}$ is a vector of vacancy characteristics as defined in section 3. $\gamma_{i,t}$ are firm-time, $\gamma_{c,t}$ are commuting-zone(CZ)-time, and $\gamma_{ind,t}$ are industry-time, $\gamma_{occ,t}$ are occupation-time, $\gamma_{occ,c}$ are occupation-CZ, and $\gamma_{occ,ind}$ are occupation-industry 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: Correlation between regional characteristics and the presence of firms with high labor market power in those regions

	HHI	GDP per Capita	House Prices	Labor Force	Tightness	Unemployment Rate
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}\{\text{High LMP Firm}\}$	0.022***	-0.151**	-0.446***	-1.291***	-0.090***	0.001
	(0.006)	(0.073)	(0.123)	(0.258)	(0.019)	(0.002)
Obs.	29,315	26,283	23,122	29,277	29,277	29,277

This table reports the results of the following regression:$y_{rt} = \alpha + \beta\mathbb{1}\{\text{High LMP Firm}\}_{rt} + \varepsilon_{rt}$ Regression is using the collapsed panel data at the region-time level. The variable $\mathbb{1}\{\text{High LMP Firm}\}$ is a dummy that takes the value of one if at least one "High LMP firm" is present in a region. "High LMP Firms" are defined as an establishment (firm-region-level) that belongs to the top 5th percentile of the distribution of vacancy shares across all regions. The regional characteristics used as dependent variable Y are GDP per Capita, House Prices, Labor Force - all standardized, Labor Market Tightness, calculated as the ratio between available vacancies and the number of workers searching for job, and Unemployment Rate. Standard errors are reported in the parenthesis and are clustered at the Commuting Zone level. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Labor Demand Effect of Monetary Policy

	Log Vacancies$_{i,c,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MP easing$_t$	0.351***	0.647***		0.696***			
	(0.036)	(0.032)		(0.035)			
LMP$_{i,c,t-1}$	23.166***	14.505***	14.958***	20.318***	20.866***	21.439***	22.713***
	(1.816)	(1.252)	(1.275)	(1.534)	(1.560)	(1.667)	(1.639)
MP easing$_t$ × LMP$_{i,c,t-1}$	13.913***	3.400*	5.439***	5.442**	7.624***	8.722**	7.895**
	(3.111)	(1.789)	(1.834)	(2.330)	(2.398)	(3.389)	(3.839)
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	377,669	355,254	355,254	355,254	355,254	199,839	199,839

This table reports estimates of the following regression: Log Vacancies$_{i,c,t} = \alpha + \beta$ MP easing$_t \times$ LMP$_{i,c,t-1}$ + $\theta X_{i,c,t} + \gamma_{i,t} + \gamma_{c,t} + \varepsilon_{i,c,t}$, 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 easing$_t$ is the negative of the monetary policy shock by Jarociński and Karadi (2020), and thus a positive value reflects monetary policy easing. LMP$_{i,c,t-1}$ is defined as the cumulative vacancy 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 5: Cumulative Labor Demand Effect of Monetary Policy, One Year Horizon

	$\sum_{h=0}^{3}$ Log Vacancies$_{i,c,t+h}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MP easing$_t$	-0.198	0.746***		0.940***			
	(0.164)	(0.131)		(0.133)			
LMP$_{i,c,t-1}$	80.868***	46.129***	48.791***	69.003***	72.139***	75.894***	78.076***
	(6.709)	(4.358)	(4.492)	(5.465)	(5.613)	(5.916)	(5.729)
MP easing$_t$ × LMP$_{i,c,t-1}$	72.928***	30.573***	18.408**	38.610***	27.042***	34.824***	35.245***
	(12.821)	(7.398)	(7.529)	(9.688)	(9.843)	(12.230)	(13.644)
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	377,669	355,254	355,254	355,254	355,254	199,839	199,839

This table reports estimates of the following regression: $\sum_{h=0}^{3}$ Log Vacancies$_{i,c,t+h}$ $= \alpha + \beta$ MP easing$_t$ × LMP$_{i,c,t-1}$ $+ \theta X_{i,c,t} + \gamma_{i,t} + \gamma_{c,t} + \varepsilon_{i,c,t}$, 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. Note the sum includes 4 quarters and thus estimates reflect the effect over a year. MP easing$_t$ is the negative of the monetary policy shock by Jarociński and Karadi (2020), in which a positive value reflects monetary policy easing. LMP$_{i,c,t-1}$ is defined as the cumulative vacancy 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 6: Labor Demand Effect of Monetary Policy across Vacancy Types

	Log Vacancies$_{i,c,t,j}$			
	(1)	(2)	(3)	(4)
LMP$_{i,c,t-1}$	18.036***	19.173***	18.391***	21.736***
	(1.282)	(1.337)	(1.311)	(1.523)
Type$_j$	-0.148***		-0.243***	
	(0.018)		(0.014)	
MP easing$_t$ × LMP$_{i,c,t-1}$	6.430**	7.785***	7.495***	8.701**
	(2.868)	(2.843)	(2.703)	(3.631)
MP easing$_t$ × Type$_j$	-0.413***		-0.130***	
	(0.040)		(0.040)	
LMP$_{i,c,t-1}$ × Type$_j$		-2.286***		-7.932***
		(0.575)		(0.712)
MP easing$_t$ × LMP$_{i,c,t-1}$ × Type$_j$		-2.938*		-3.576
		(1.623)		(2.400)
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 estimates of the following regression: Log Vacancies$_{i,c,t,j}$ $= \alpha + \beta$ MP easing$_t$ × LMP$_{i,c,t-1}$ + δ MP easing$_t$ × LMP$_{i,c,t-1}$ × Type$_j$ $+ X_{i,c,t} + \gamma_{i,t} + \gamma_{c,t} + \gamma_{j,t} + \varepsilon_{i,c,t}$, 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 easing$_t$ is the negative of the monetary policy shock by Jarociński and Karadi (2020), in which a positive value reflects monetary policy easing. LMP$_{i,c,t-1}$ is defined as the cumulative vacancy share of firm i in commuting zone c at quarter $t-1$. Type$_j$ is a dummy taking the value of one if the vacancy requires the particular "Vacancy Type" reported in the similar named column and zero otherwise. 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 7: Cumulative Labor Demand Effect of Monetary Policy across Vacancy Types, One Year Horizon

	$\sum_{h=0}^{3}$ Log Vacancies$_{i,c,t+h,j}$			
	(1)	(2)	(3)	(4)
LMP$_{i,c,t-1}$	60.537***	70.127***	57.072***	77.867***
	(4.516)	(5.117)	(4.418)	(5.653)
Type$_j$	-0.705***		-1.173***	
	(0.067)		(0.049)	
MP easing$_t$ × LMP$_{i,c,t-1}$	27.150**	38.581***	23.695**	39.483***
	(10.664)	(11.387)	(10.184)	(12.935)
MP easing$_t$ × Type$_j$	-0.467***		-0.463***	
	(0.128)		(0.123)	
LMP$_{i,c,t-1}$ × Type$_j$		-19.180***		-41.591***
		(3.412)		(3.610)
MP easing$_t$ × LMP$_{i,c,t-1}$ × Type$_j$		-22.864***		-31.576***
		(5.582)		(7.925)
Obs.	30,184,882	30,184,882	30,184,882	30,184,882
Vacancy Type	college	college	software	software
Firm × Time FE	✓	✓	✓	✓
CZ × Time FE	✓	✓	✓	✓
Vac. Type × Time FE		✓		✓

This table reports estimates of the following regression: $\sum_{h=0}^{3}$ Log Vacancies$_{i,c,t+h,j}$ $= \alpha + \beta$MP easing$_t$ × LMP$_{i,c,t-1} + \delta$ MP easing$_t$ × LMP$_{i,c,t-1}$ × Type$_{i,c,t,j} + \theta X_{i,c,t} + \gamma_{i,t} + \gamma_{c,t} + \gamma_{j,t} + \varepsilon_{i,c,t}$, where Log Vacancies$_{i,c,t,j}$ is defined as the log number of vacancies posted by firm i, in commuting zone c in quarter t. Vacancy Type$_{i,c,t,j} = 1$ for the type "college" means that vacancies require a college degree and for the type "software" means that vacancies require software skills. Note the sum includes 4 quarters and thus estimates reflect the effect over a year. MP easing$_t$ is the negative of the monetary policy shock by Jarociński and Karadi (2020), in which a positive value reflects monetary policy easing. LMP$_{i,c,t-1}$ is defined as the cumulative vacancy share of firm i in commuting zone c at quarter $t-1$. Type$_j$ is a dummy taking the value of one if the vacancy requires the particular "Vacancy Type" reported in the similar named column and zero otherwise. For more details see section 3. $\gamma_{i,t}$ are firm-time, $\gamma_{c,t}$ are commuting-zone(CZ)-time, and $\gamma_{j,t}$ are vacancy type-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 8: Wage Effect of Monetary Policy

	Log Wages$_{i,c,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MP easing$_t$	0.001	0.146***		0.148***			
	(0.038)	(0.023)		(0.024)			
LMP$_{i,c,t-1}$	0.277**	-0.084	-0.011	0.056	0.112*	0.354***	0.390***
	(0.137)	(0.085)	(0.093)	(0.061)	(0.065)	(0.077)	(0.081)
MP easing$_t$ × LMP$_{i,c,t-1}$	0.191	-0.579**	0.009	-0.495*	0.090	0.433	0.363
	(0.389)	(0.271)	(0.271)	(0.279)	(0.277)	(0.349)	(0.482)
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	281,380	216,315	216,315	216,315	216,315	97,858	97,856

This table reports estimates of the following regression: Log Wages$_{i,c,t} = \alpha + \beta$ MP easing$_t \times \text{LMP}_{i,c,t-1} + \theta X_{i,c,t} + \gamma_{i,t} + \gamma_{c,t} + \varepsilon_{i,c,t}$, where Log Wages$_{i,c,t}$ is defined as the log wage of vacancies posted by firm i, in commuting zone c in quarter t, relative to the commuting zone-time average wage. MP easing$_t$ is the negative of the monetary policy shock by Jarociński and Karadi (2020), in which a positive value reflects monetary policy easing. LMP$_{i,c,t-1}$ is defined as the cumulative vacancy 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 9: Cumulative Wage Effect of Monetary Policy, One Year Horizon

	$\sum_{h=0}^{3}$ Log Wages$_{i,c,t+h}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MP easing$_t$	-0.076	0.118**		0.121**			
	(0.075)	(0.051)		(0.051)			
LMP$_{i,c,t-1}$	1.155***	0.039	0.142	0.376**	0.460**	0.905***	0.905***
	(0.399)	(0.227)	(0.237)	(0.187)	(0.201)	(0.235)	(0.251)
MP easing$_t$ × LMP$_{i,c,t-1}$	1.547*	0.321	0.952	0.509	1.145*	1.680***	0.941
	(0.871)	(0.626)	(0.637)	(0.633)	(0.641)	(0.572)	(0.748)
Obs.	5531158	5531158	5107348	5107348	5107348	3951104	3950697
Firm FE		✓	✓	✓	✓		
Time FE			✓		✓		
CZ FE				✓	✓	✓	
Firm × Time FE						✓	✓
CZ × Time FE							✓
No. Firms	285,561	246,906	246,906	246,906	246,906	104,354	104,353

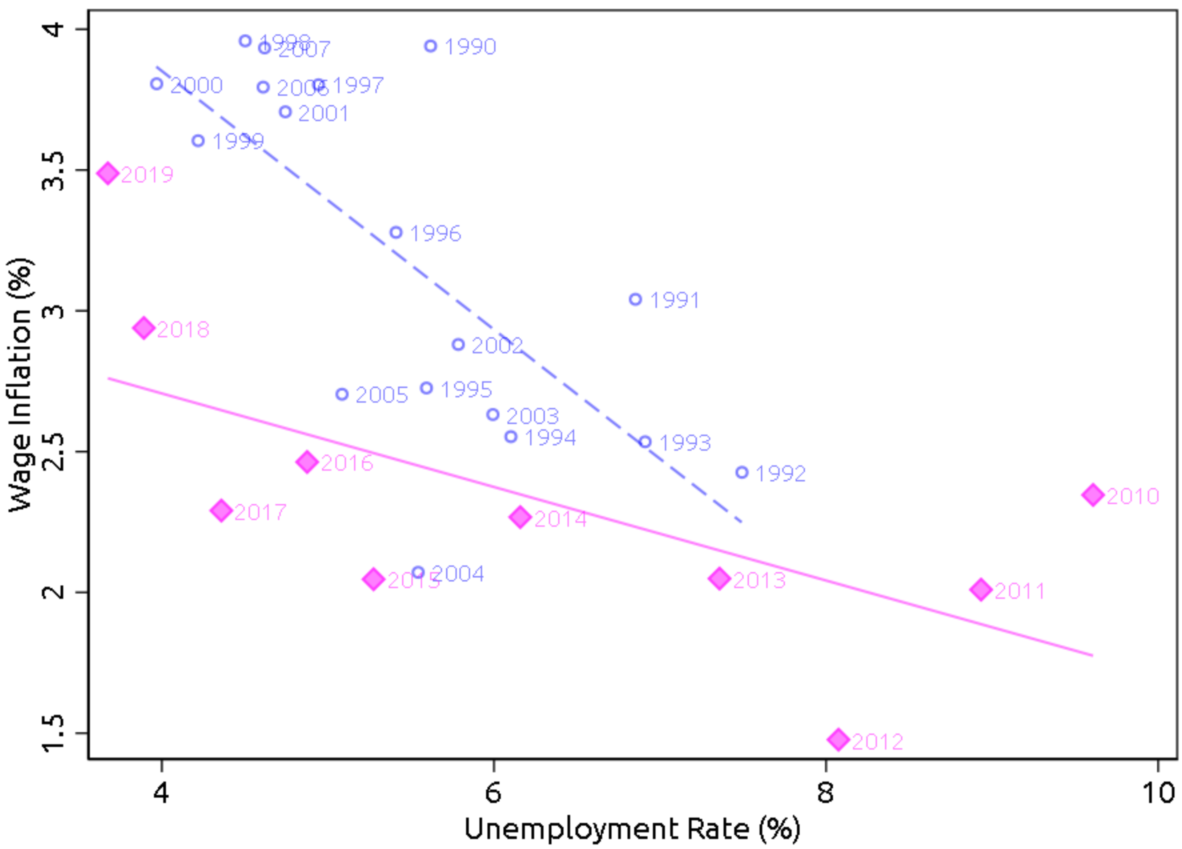
This table reports estimates of the following regression: $\sum_{h=0}^{3}$ Log Wage Measure$_{i,c,t+h} = \alpha + \beta$ MP easing$_t \times \text{LMP}_{i,c,t-1} + \theta X_{i,c,t} + \gamma_{i,t} + \gamma_{c,t} + \varepsilon_{i,c,t}$, where Log Wages$_{i,c,t}$ is defined as the log wage of vacancies posted by firm i, in commuting zone c in quarter t, relative to the commuting zone-time average wage. Note the sum includes 4 quarters and thus estimates reflect the effect over a year. MP easing$_t$ is the negative of the monetary policy shock by Jarociński and Karadi (2020), in which a positive value reflects monetary policy easing. LMP$_{i,c,t-1}$ is defined as the cumulative vacancy 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 10: 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)
$\mathbb{1}$ LMP$_{c,t}$	-0.090***	-0.091***	-0.078	-0.102**
	(0.031)	(0.031)	(0.052)	(0.050)
Unemployment Rate$_{c,t}$ $\times$ $\mathbb{1}$ LMP$_{c,t}$	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			✓	✓

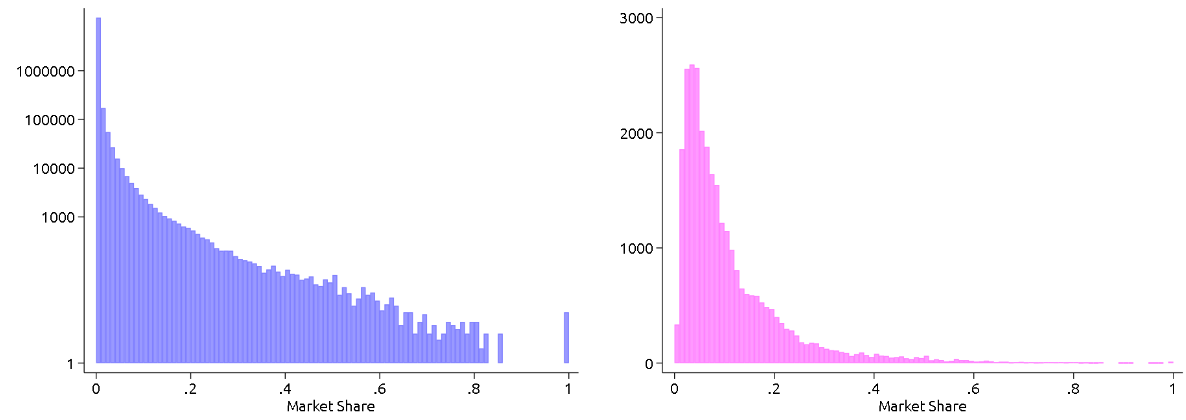
This table reports estimates of the following regression: Wage Growth$_{c,t}$ $= \alpha + \theta$ Unemployment Rate$_{c,t}$ $+ \delta\, \mathbb{1}\{\text{LMP}_{c,t}\} + \beta$Unemployment Rate$_{c,t} \times \mathbb{1}\{\text{LMP}_{c,t}\} + \gamma_c + \gamma_t + \epsilon_{c,t}$ where Wage Growth$_{c,t}$ is the annual wage growth of posted vacancies from Burning Glass Technology at the commuting zone-year level. $\mathbb{1}\{\text{LMP}_{c,t}\}$ 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. γ_c are commuting zone and γ_t are time fixed effects. 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 are for the years 2010-2019 and 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. 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: Histogram of the Distribution of Labor Market Power

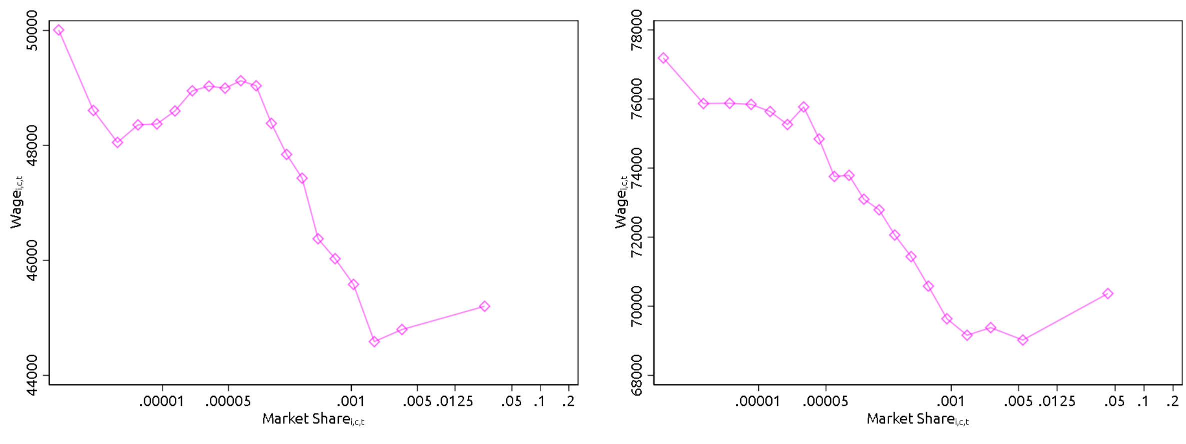


(a) Histogram of LMP

(b) Histogram of LMP of Firms with LMP

The left panel plots the histogram of the share of vacancies at the firm-commuting zone level that we use to proxy for LMP. Shares are defined as Vacancy 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. The y-axis scale is in logs and represents the number of firms in the corresponding bin. The right panel plots the histogram of that share of vacancies at the firm-commuting zone level for only firms with high labor market power, defined as those in the 95th percentile of the distribution on the left chart.

Figure 3: Vacancy Share and Wages

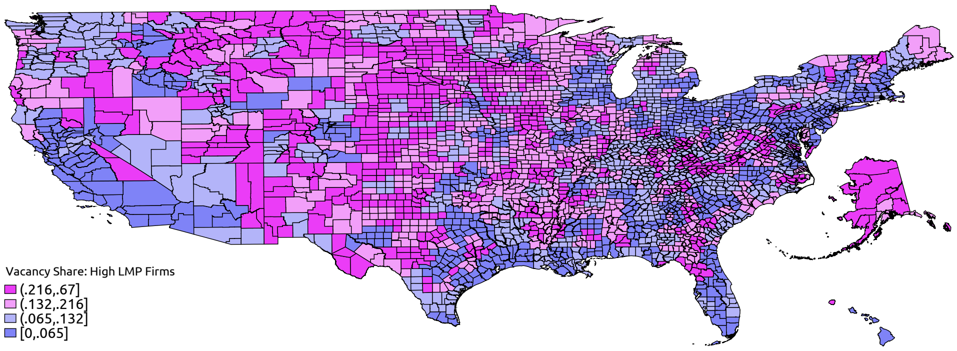


(a) Vacancies *without* a college requirement

(b) Vacancies *with* a college requirement

This figure plots a local polynomial smooth of wages on vacancy 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 vacancy share defined as Vacancy 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.

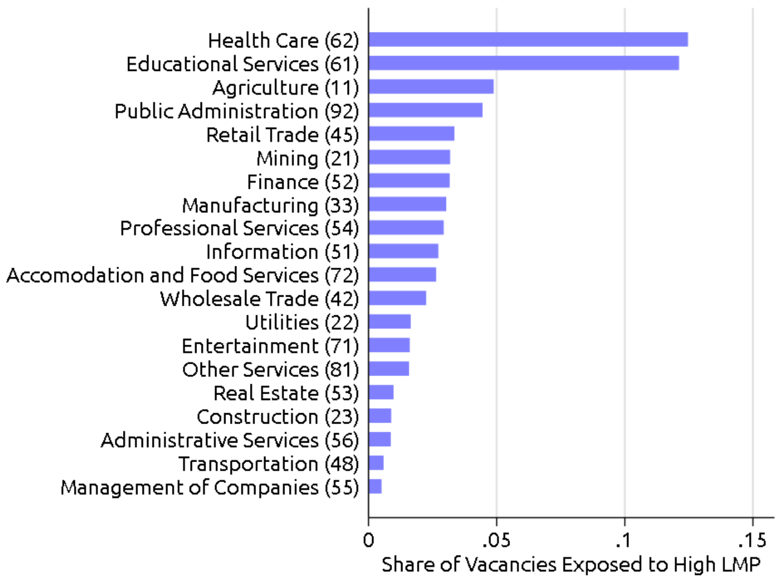
Figure 4: Geography of Labor Market Power



(a) Share of Vacancies Controlled by Firms with LMP

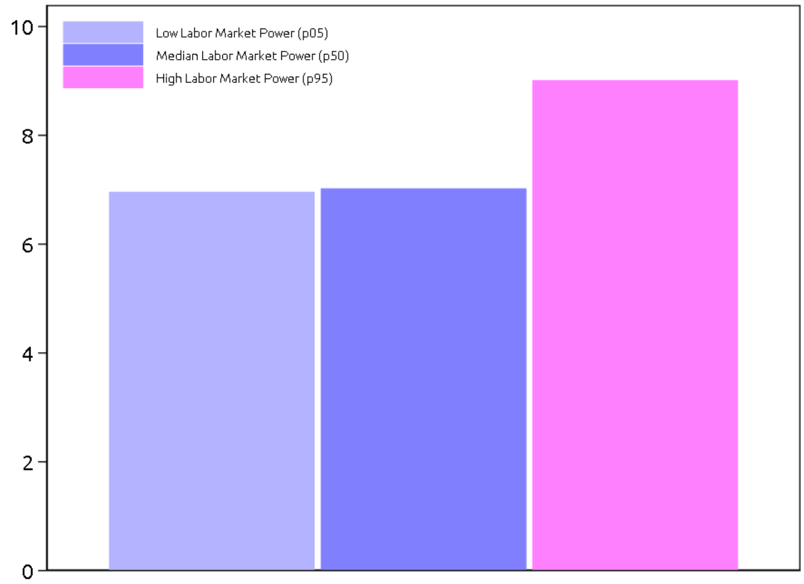
The figure reports Labor Market Power across the United States. A firm is deemed to have labor market power in a region if its establishment accounts for a very high share of local vacancies, defined as being in the top 5th percentile of the distribution of share of vacancies across all firm-region-time. The map reports the share of vacancies controlled by firms with labor market power.

Figure 5: Labor Market Power by Sector



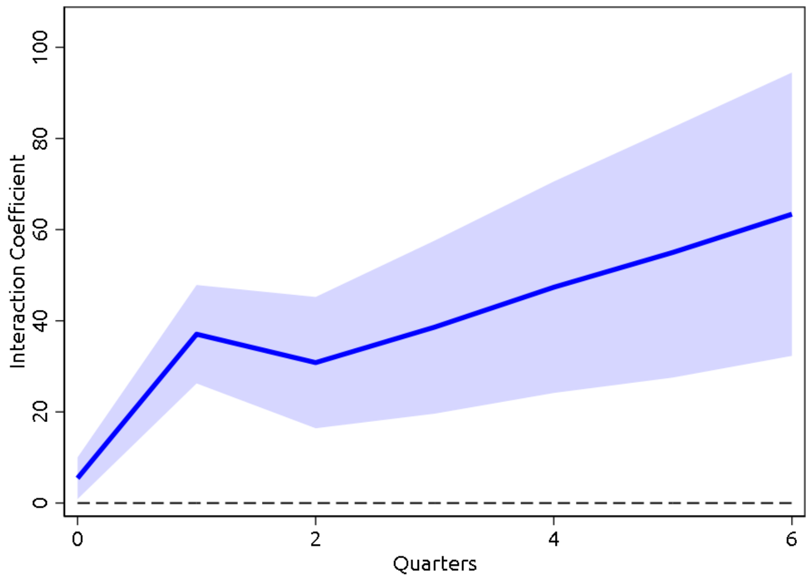
This figure plots the share of firms with high labor market power within each industry.

Figure 6: Response of Vacancy Postings to a 10 bps Easing of Monetary Policy



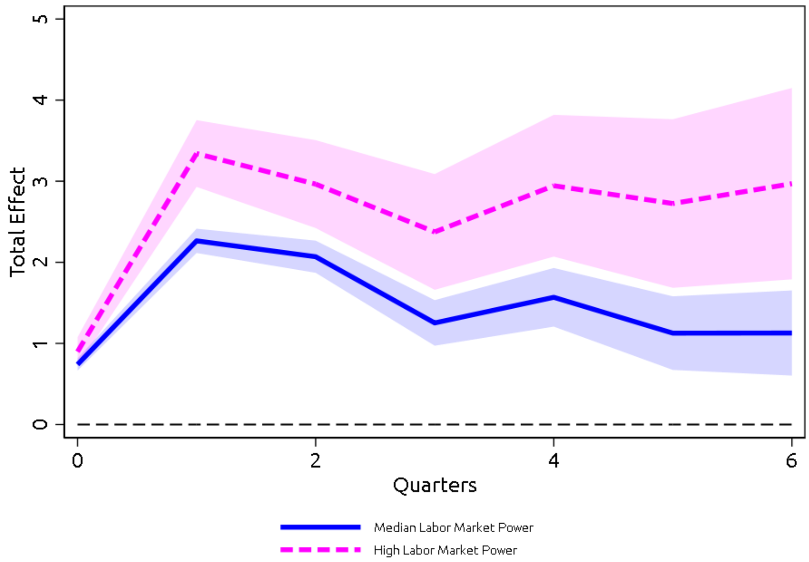
This figure plots the total effect of an accommodating monetary policy shock on vacancy postings given by: β MP easing$_t$ $\times$ LMP$_{i,c,t-1}$. LMP$_{i,c,t-1}$ is defined as the cumulative vacancy share of firm i in the commuting zone c at quarter $t-1$. For more details see section 3. The three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

Figure 7: Response of Vacancies: Interaction Coefficient of Labor Market Power and a Monetary Policy Easing Shock Across Horizons



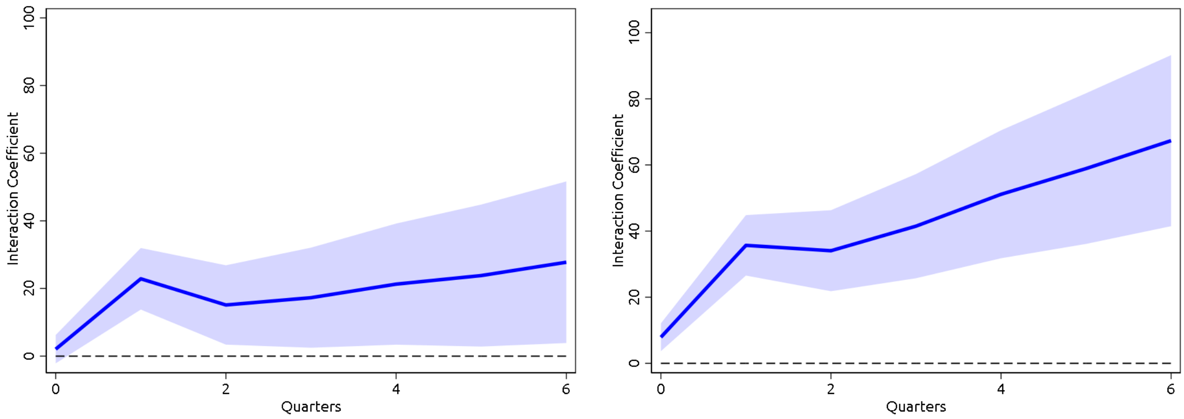
This figure plots β_H of $\sum_{h=0}^{H}$ Log Vacancies$_{i,c,t+h}$ $= \alpha_H + \beta_H$ MP easing$_t$ $\times$ LMP$_{i,c,t-1} + \theta_H X_{i,c,t} + \gamma_{i,t+H} + \gamma_{c,t+H} + \varepsilon_{i,c,t+H}$ where Log Vacancies$_{i,c,t}$ is defined as the log number of vacancies posted by firm i, in commuting zone c in quarter t. MP easing$_t$ is the negative of the monetary policy shock by Jarociński and Karadi (2020), in which a positive value reflects monetary policy easing. LMP$_{i,c,t-1}$ is defined as the cumulative vacancy 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. Shaded areas represent a 95% confidence interval.

Figure 8: Response of Vacancy Postings to a Monetary Policy Easing Shock Across Horizons Depending on Labor Market Power



This figure plots the estimated response of vacancy postings for a firm with High LMP (95th percentile of the vacancy share distribution) in pink and median LMP (50th percentile of the vacancy share distribution) of $\sum_{h=0}^{H} \text{Log Vacancies}_{i,c,t+h} = \alpha_H + \omega_H \text{ MP easing}_t + \beta_H \text{ MP easing}_t \times \text{LMP}_{i,c,t-1} + \theta_H X_{i,c,t} + \gamma_{i,t+H} + \gamma_{c,t+H} + \varepsilon_{i,c,t+H}$ 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 easing$_t$ is the negative of the monetary policy shock by Jarociński and Karadi (2020), in which a positive value reflects monetary policy easing. LMP$_{i,c,t-1}$ is defined as the cumulative vacancy share of firm i in commuting zone c at quarter $t-1$. For more details see section 3. The pink line is $\alpha + \beta \times \text{LMP}_{i,c,t-1}(P95)$ and the blue line is $\alpha + \beta \times \text{LMP}_{i,c,t-1}(P50)$. Standard errors are double clustered at the firm and commuting zone level. Shaded areas represent a 95% confidence interval.

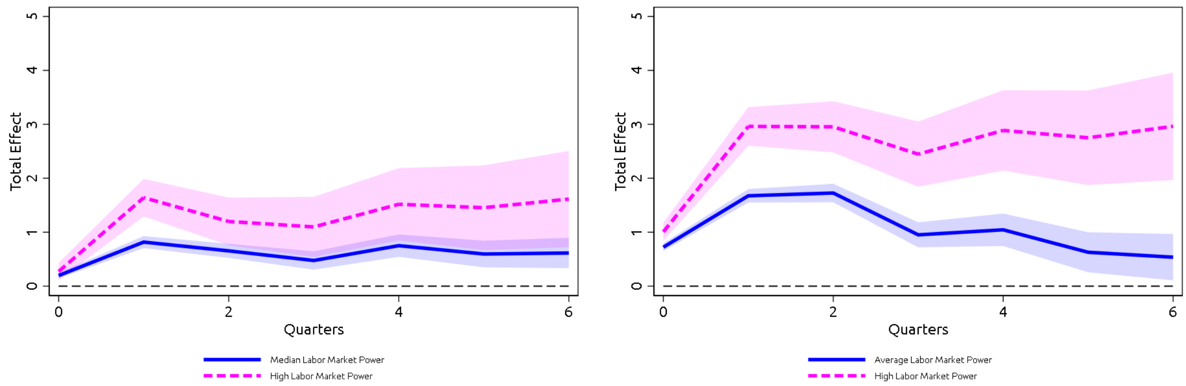
Figure 9: Response of Vacancy Postings to a Monetary Policy Easing Shock Across Horizons Depending on Requirement of a College Degree



(a) Vacancies *with* college requirement (b) Vacancies *without* college requirement

This figure plots $\hat{\beta}_H$ and $\hat{\beta}_H + \hat{\omega}_H$ from estimating $\sum_{h=0}^{H}$ Log Vacancies$_{i,c,t+h} = \alpha_H + \beta_H$ MP easing$_t \times$LMP$_{i,c,t-1}+$ ω_H MP easing$_t$ $\times$ LMP$_{i,c,t-1}$ $\times$ Vacancy Type $+ \theta_H X_{i,c,t} + \gamma_{i,t+H} + \gamma_{c,t+H} + \varepsilon_{i,c,t+H}$ 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. Vacancy Type = 1 means that the vacancy requires a college degree. **The left panel** represents the response of the vacancies that require a college degree, **the right panel** represents vacancies that do *not* require a college degree. MP easing$_t$ is the negative of the monetary policy shock by Jarociński and Karadi (2020), in which a positive value reflects monetary policy easing. LMP$_{i,c,t-1}$ is defined as the cumulative vacancy 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. Shaded areas represent a 95% confidence interval.

Figure 10: Response of Vacancy Postings to a Monetary Policy Easing Shock Across Horizons Depending on Requirement of a College Degree and on Labor Market Power

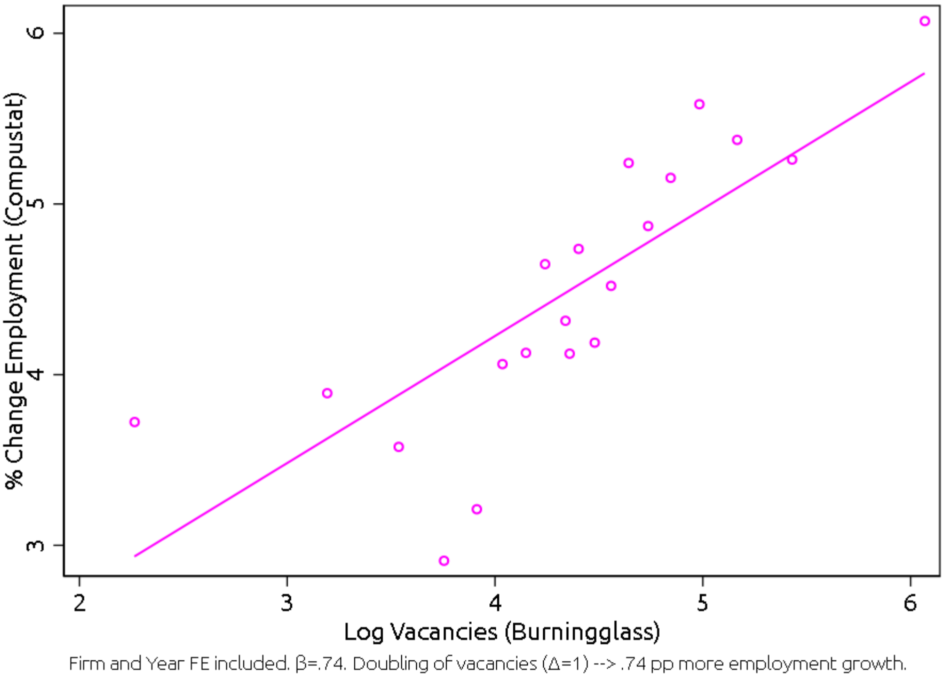


(a) Vacancies *with* college requirement

(b) Vacancies *without* college requirement

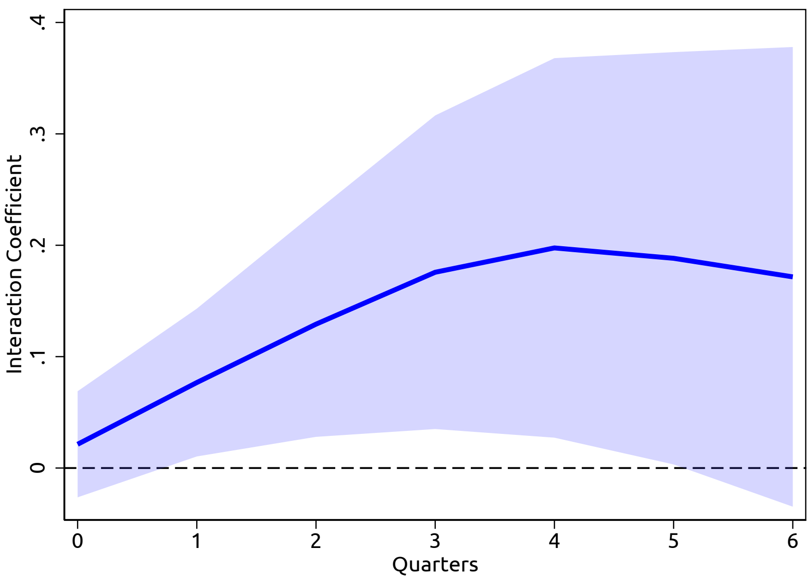
This figure plots the estimated response of vacancy postings for a firm a large extent of market power (95th percentile) in pink and medium market power (50th percentile) in blue from the following regression $\sum_{h=0}^{H}$ Log Vacancies$_{i,c,t+h} = \alpha_H + \beta_H$ MP easing$_t \times \text{LMP}_{i,c,t-1} + \omega_H$ MP easing$_t \times \text{LMP}_{i,c,t-1} \times$ Vacancy Type $+$ $\theta_H X_{i,c,t} + \gamma_{i,t+H} + \gamma_{c,t+H} + \varepsilon_{i,c,t+H}$ 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. Vacancy Type $= 1$ means that the vacancy requires a college degree. **The left panel** represents the response of the vacancies that require a college degree, **the right panel** represents vacancies that do *not* require a college degree. MP easing$_t$ is the negative of the monetary policy shock by Jarociński and Karadi (2020), in which a positive value reflects monetary policy easing. $\text{LMP}_{i,c,t-1}$ is defined as the cumulative vacancy share of firm i in commuting zone c at quarter $t-1$. For more details see section 3. The pink lines are defined $\alpha + \beta \times \text{LMP}_{i,c,t-1}(P95)$ for non-college vacancies and $\alpha + \beta \times \text{LMP}_{i,c,t-1}(P95) + \omega \times \text{LMP}_{i,c,t-1}(P95)$. The blue lines are defined as $\alpha + \beta \times \text{LMP}_{i,c,t-1}(P50)$ and $\alpha + \beta \times \text{LMP}_{i,c,t-1}(P50) + \omega \times \text{LMP}_{i,c,t-1}(P50)$. Standard errors are double clustered at the firm and commuting zone level. Shaded areas represent a 95% confidence interval.

Figure 11: Sensitivity of Employment to Vacancy Postings



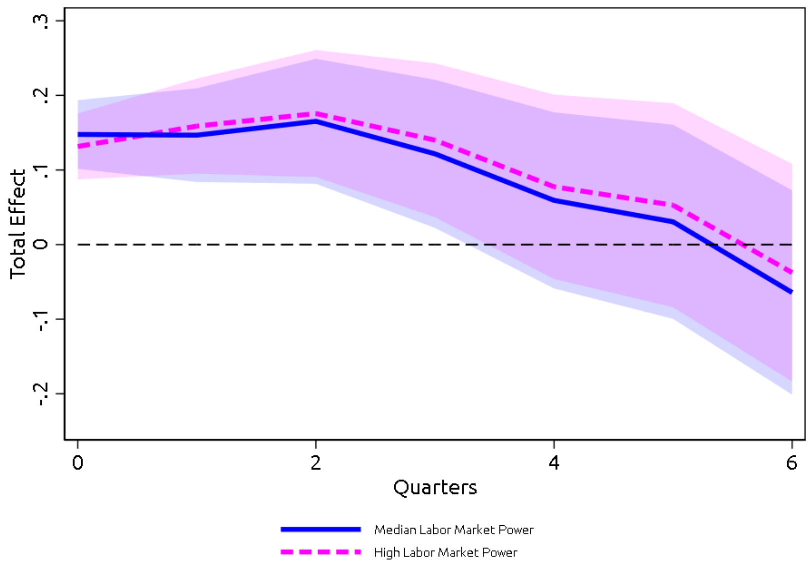
This figure plots a binscatterplot between the log change in employment from Compustat on Log Vacancy postings from BGT: $\Delta Employment_{i,t} = \alpha_i + \alpha_t + \beta_1 \text{Log Vacancies}_{i,t} + \epsilon_{i,t}$ where $\Delta Employment_{i,t}$ is the log change in employment of firm i between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

Figure 12: Interaction Coefficient of Labor Market Power and a Monetary Policy Easing Shock Across Horizons



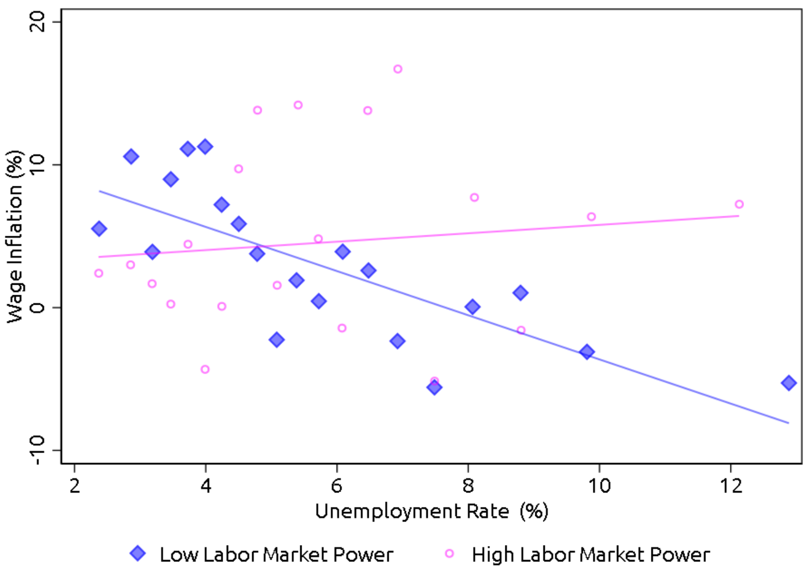
This figure plots $\hat{\beta}_H$ from estimating $\sum_{h=0}^{H} \Delta\text{Employment}_{i,t+h} = \alpha_H + \beta_H \text{ MP easing}_t \times \text{LMP}_{i,t-1} + \theta_H X_{i,t} + \gamma_{i,H} + \gamma_{t+H} + \varepsilon_{i,t+H}$ where $\Delta\text{Employment}_{i,t+h}$ is defined as the log difference between employment in time t+h and t-1. MP easing_t is the negative of the monetary policy shock by Jarociński and Karadi (2020), in which a positive value reflects monetary policy easing. $\text{LMP}_{i,t-1}$ is defined as one if the firm is in the top 5% of labor market power in at least one commuting zone. For more details see section 3. Standard errors are clustered at the firm level. Shaded areas represent a 95% confidence interval.

Figure 13: Response of Wages to a Monetary Policy Easing Shock Across Horizons



This figure plots the estimated response of log deviation of wages from the regional average for a firm with large labor market power (95th percentile) in pink and medium labor market power (50th percentile) in blue from the following regression $\sum_{h=0}^{H} \text{Log Wage}_{i,c,t+h} = \alpha_H + \beta_H \text{ MP easing}_t \times \text{LMP}_{i,c,t-1} + \theta_H X_{i,c,t} + \gamma_{i,t+H} + \gamma_{c,t+H} + \varepsilon_{i,c,t+H}$ where Log $\text{Wage}_{i,c,t+h}$ is defined as the log wage of vacancies posted by firm i, in commuting zone c in quarter t, relative to the commuting zone-time average wage. MP easing_t is the negative of the monetary policy shock by Jarociński and Karadi (2020), in which a positive value reflects monetary policy easing. $\text{LMP}_{i,c,t-1}$ is defined as the cumulative vacancy share of firm i in commuting zone c at quarter $t-1$. For more details see section 3. The pink line is $\alpha + \beta \times \text{LMP}_{i,c,t-1}(P95)$ and the blue line is defined as $\alpha + \beta \times \text{LMP}_{i,c,t-1}(P50)$. Standard errors are double clustered at the firm and commuting zone level. Shaded areas represent a 95% confidence interval.

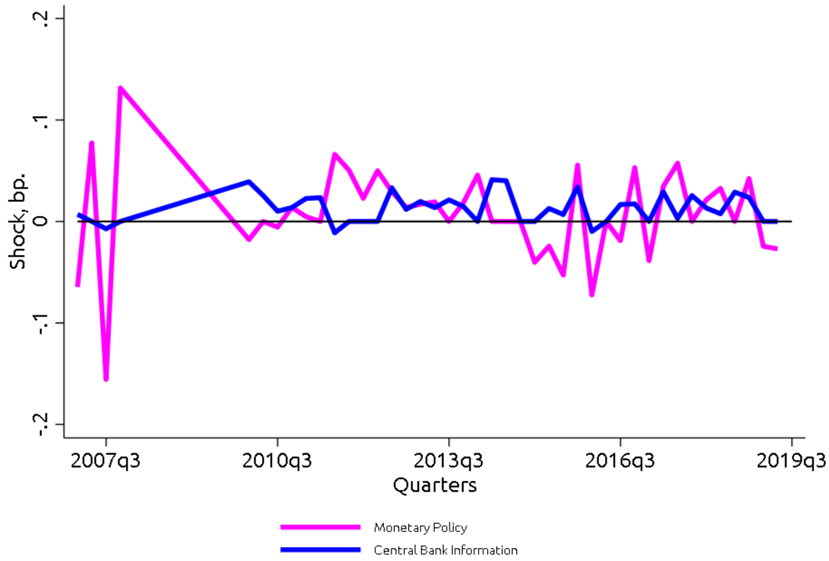
Figure 14: Wage Phillips Curve by Labor Market Power



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.

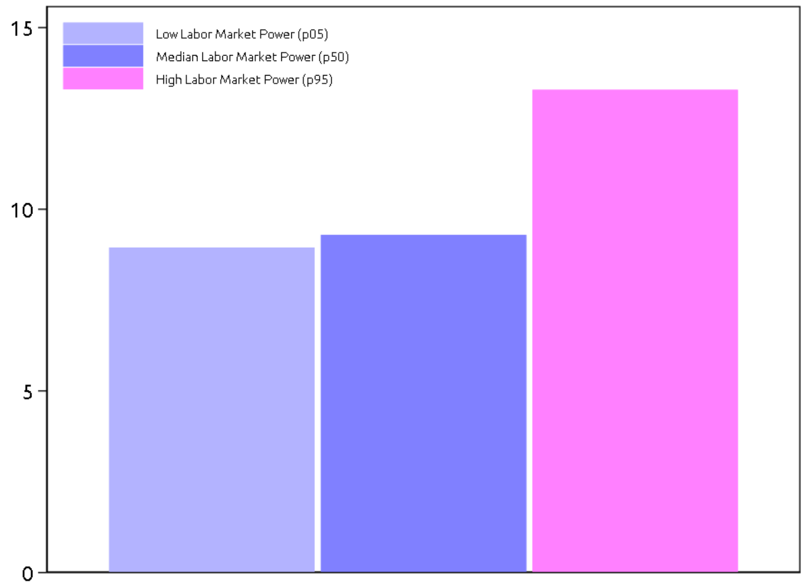
A Appendix Tables and Figures

Figure A1: Monetary Policy Shocks in Percentage Points (JK 2020)



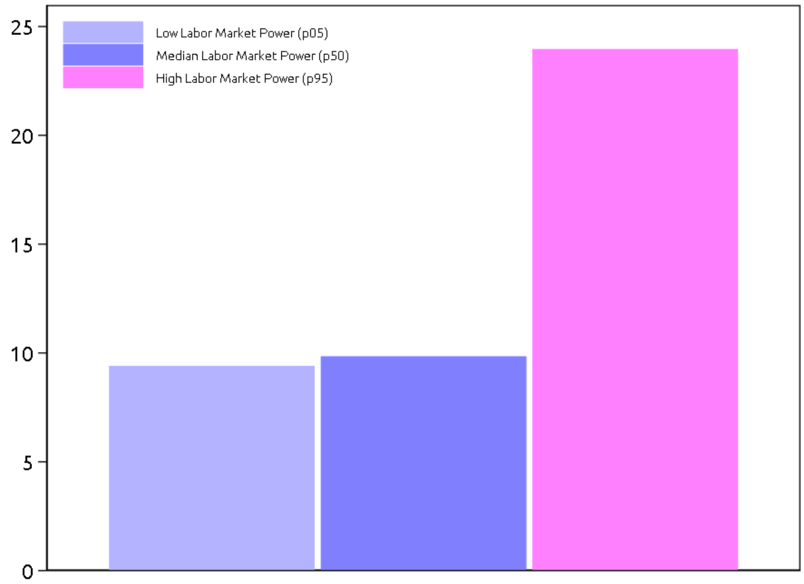
This figure plots Shocks time series used in the paper. The shock series is developed by Jarociński and Karadi (2020). The positive value of the shock reflects monetary policy easing. The unit is in percentage points. Monetary Policy reflects the shock component that can be assigned to the direct effects of Monetary Policy. Central Bank Information component measures the shock component associated with the effects of the Fed information.

Figure A2: Response of Vacancy Postings to Monetary Policy Easing



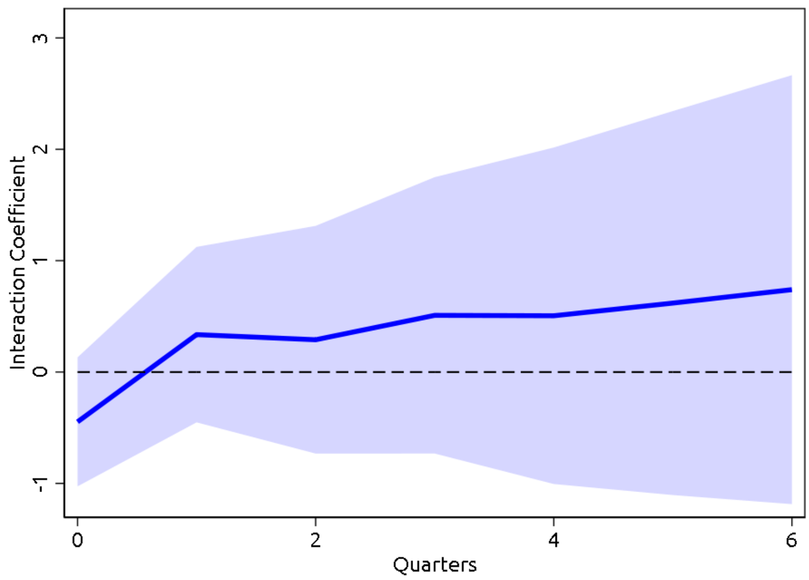
This figure plots the total effect of the accommodating monetary policy on vacancy postings given by: β MP easing$_t$ $\times$ LMP$^{alt}_{i,c,t-1}$. LMP$^{alt}_{i,c,t-1}$ is defined as the cumulative vacancy share of firm i in the corresponding industry in the commuting zone c at quarter $t-1$. For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

Figure A3: Cumulative Response of Vacancy Postings in Response to Monetary Policy Easing, One Year Horizon



This figure plots the total effect of the accommodating monetary policy one year ahead on vacancy postings given by: β MP easing$_t \times \text{LMP}_{i,c,t-1}$. $\text{LMP}_{i,c,t-1}$ is defined as the cumulative vacancy 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: low (5th percentile of the distribution of vacancy shares), median (50th percentile of the distribution of vacancy shares) and high (95th percentile of the distribution of vacancy shares).

Figure A4: Response of Wages: Interaction Coefficient of Labor Market Power and a Monetary Policy Easing Shock Across Horizons



This figure plots $\hat{\beta}_H$ from estimating $\sum_{h=0}^{H} \text{Log Wages}_{i,c,t+h} = \alpha_H + \beta_H \text{ MP easing}_t \times \text{LMP}_{i,c,t-1} + \theta_H X_{i,c,t} + \gamma_{i,t+H} + \gamma_{c,t+H} + \varepsilon_{i,c,t+H}$ where $\text{Log Wages}_{i,c,t}$ is defined as the log wage of vacancies posted by firm i, in commuting zone c in quarter t, relative to the commuting zone-time average wage. MP easing$_t$ is the negative of the monetary policy shock by Jarociński and Karadi (2020), in which a positive value reflects monetary policy easing. $\text{LMP}_{i,c,t-1}$ is defined as the cumulative vacancy 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. Shaded areas represent a 95% confidence interval.

Table A1: Robustness to the Choice of Monetary Policy Shock

	Log Vacancies$_{i,c,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
MP easing$_t$ × LMP$_{i,c,t}$	1.415***	1.387***	-0.693***	2.942***	0.849***	1.430***
	(0.405)	(0.361)	(0.206)	(0.605)	(0.185)	(0.333)
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	✓	✓	✓	✓	✓	✓
Shock	Nakamura and Steinsson (2018)	Bu et al. (2021)	Jarocinski (2021)	Jarocinski (2021)	Jarocinski (2021)	Jarocinski (2021)

This table reports estimates of the following regression: Log Vacancies$_{i,c,t} = \alpha + \beta$ MP easing$_t$ $\times$ LMP$_{i,c,t-1}$ + $\theta X_{i,c,t} + \gamma_{i,t} + \gamma_{c,t} + \varepsilon_{i,c,t}$, 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 easing$_t$ are different monetary policy shocks, including Nakamura and Steinsson (2018), Bu et al. (2021) and Jarocinski (2021), in which a positive value reflects monetary policy easing. The four shocks from Jarocinski (2021) are: a standard contractionary monetary policy shock (column 3), a forward guidance shock that reflects a commitment future policy rates (column 4), a shock to longer-term treasury yields mostly affected by asset purchase announcements (column 5), and a forward guidance shock that captures the stance of future monetary policy in the sense of a prediction of the appropriate stance of policy (column 6). LMP$_{i,c,t-1}$ is defined as the cumulative vacancy share of firm i in the corresponding 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 A2: Labor Demand Effect of Monetary Policy Using An Alternative Definition of Labor Market Power at the Industry Level

	Log Vacancies$_{i,c,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MP easing$_t$	0.447***	0.830***		0.894***			
	(0.050)	(0.040)		(0.042)			
LMP Industry$_{i,c,t}$	0.657***	-0.098**	-0.047	0.979***	1.076***	1.202***	1.223***
	(0.061)	(0.049)	(0.051)	(0.045)	(0.045)	(0.050)	(0.051)
MP easing$_t$ × LMP Industry$_{i,c,t}$	0.807***	0.110	0.206	0.520***	0.582***	0.607***	0.868***
	(0.166)	(0.135)	(0.138)	(0.150)	(0.155)	(0.124)	(0.121)
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	307,226	252,448	252,448	252,448	252,448	92,179	92,178

This table reports estimates of the following regression: Log Vacancies$_{i,c,t} = \alpha + \beta$ MP easing$_t$ $\times$ LMP$^{alt}_{i,c,t-1}$ + $\theta X_{i,c,t} + \gamma_{i,t} + \gamma_{c,t} + \varepsilon_{i,c,t}$, 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 easing$_t$ is the negative of the monetary policy shock by Jarociński and Karadi (2020), in which a positive value reflects monetary policy easing. LMP$^{alt}_{i,c,t-1}$ is defined as the cumulative vacancy 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.

Table A3: Labor Demand Effect of Monetary Policy Excluding Public Administration

	Log Vacancies$_{i,c,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MP easing$_t$	0.330***	0.625***		0.672***			
	(0.036)	(0.031)		(0.035)			
LMP$_{i,c,t}$	24.517***	15.485***	15.952***	21.520***	22.082***	22.658***	24.005***
	(1.700)	(1.209)	(1.231)	(1.465)	(1.491)	(1.573)	(1.589)
MP easing$_t$ × LMP$_{i,c,t}$	15.005***	3.556*	5.611***	5.766**	7.961***	9.901**	9.181**
	(3.363)	(1.965)	(1.999)	(2.594)	(2.654)	(3.914)	(4.202)
Obs.	14,617,275	14,594,671	14,594,671	14,594,671	14,594,671	12,460,654	12,460,505
Firm FE		✓	✓	✓	✓		
Time FE			✓		✓		
CZ FE				✓	✓	✓	
Firm × Time FE						✓	✓
CZ × Time FE							✓
No. Firms	369,610	347,006	347,006	347,006	347,006	195,279	195,279

This table is a robustness to Table 4 where job posters in the Public Administration sector were excluded. It reports estimates of the following regression: Log Vacancies$_{i,c,t}$ $= \alpha + \beta$ MP easing$_t \times$LMP$_{i,c,t-1} + \theta X_{i,c,t} + \gamma_{i,t} + \gamma_{c,t} + \varepsilon_{i,c,t}$, 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 easing$_t$ is the negative of the monetary policy shock by Jarociński and Karadi (2020), and thus a positive value reflects monetary policy easing. LMP$_{i,c,t-1}$ is defined as the cumulative vacancy 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 A4: Labor Demand Effect of Monetary Policy with Aggregate Controls

	Log Vacancies$_{i,c,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MP easing$_t$	0.064**	0.429***		0.432***			
	(0.031)	(0.029)		(0.031)			
LMP$_{i,c,t-1}$	38.060***	21.163***	21.580***	29.940***	30.384***	34.879***	35.724***
	(5.129)	(3.321)	(3.324)	(4.253)	(4.259)	(4.125)	(4.321)
MP easing$_t$ × LMP$_{i,c,t-1}$	35.809***	12.253***	12.309***	18.922***	18.987***	19.032***	17.615***
	(6.557)	(2.949)	(2.939)	(3.954)	(3.944)	(5.806)	(6.131)
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	377,669	355,254	355,254	355,254	355,254	199,839	199,839

This table is a robustness to Table 4 where a set of aggregate controls are added including 4 lags of GDP growth, inflation and unemployment rate. It table reports estimates of the following regression: Log Vacancies$_{i,c,t}$ $=$ $\alpha + \beta$ MP easing$_t \times$ LMP$_{i,c,t-1} + \theta X_{i,c,t} + \gamma_{i,t} + \gamma_{c,t} + \varepsilon_{i,c,t}$, 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 easing$_t$ is the negative of the monetary policy shock by Jarociński and Karadi (2020), and thus a positive value reflects monetary policy easing. LMP$_{i,c,t-1}$ is defined as the cumulative vacancy 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 A5: Dynamic Labor Demand Effect of Monetary Policy

	$\sum_{h=0}^{H}$ Log Vacancies$_{i,c,t+h}$															
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
MP easing$_t$	0.696***	0.000	1.965***	0.000	1.820***	0.000	0.940***	0.000	1.185***	0.000	0.682***	0.000	0.615**	0.000	0.853***	0.000
	(0.035)	(0.000)	(0.066)	(0.000)	(0.090)	(0.000)	(0.133)	(0.000)	(0.174)	(0.000)	(0.222)	(0.000)	(0.258)	(0.000)	(0.283)	(0.000)
LMP$_{i,c,t-1}$	20.318***	22.713***	39.246***	44.025***	55.205***	62.250***	69.003***	78.076***	82.404***	93.640***	95.492***	108.922***	108.176***	123.476***	120.259***	137.411***
	(1.534)	(1.639)	(3.019)	(3.196)	(4.306)	(4.535)	(5.465)	(5.729)	(6.580)	(6.908)	(7.647)	(8.061)	(8.666)	(9.166)	(9.628)	(10.223)
MP easing$_t$ $\times$ LMP$_{i,c,t-1}$	5.442**	7.895**	37.053***	41.740***	30.818***	33.598***	38.610***	35.245***	47.357***	43.668***	55.001***	47.717**	63.385***	54.807**	71.901***	62.939***
	(2.330)	(3.839)	(5.507)	(8.544)	(7.347)	(11.122)	(9.688)	(13.644)	(11.834)	(16.425)	(14.007)	(19.006)	(15.857)	(21.663)	(17.397)	(24.291)
Total Effect, Low LMP	0.7		2.3		2.1		1.3		1.6		1.1		1.1		1.4	
	(0.0)		(0.1)		(0.1)		(0.1)		(0.2)		(0.2)		(0.3)		(0.3)	
Total Effect, High LMP	0.9		3.3		3.0		2.4		2.9		2.7		3.0		3.5	
	(0.1)		(0.2)		(0.3)		(0.4)		(0.4)		(0.5)		(0.6)		(0.7)	
Obs.	15,070,026	12,851,727	15,070,026	12,851,727	15,070,026	12,851,727	15,070,026	12,851,727	15,070,026	12,851,727	15,070,026	12,851,727	15,070,026	12,851,727	15,070,026	12,851,727
Horizon	0	0	1	1	2	2	3	3	4	4	5	5	6	6	7	7
Firm FE	✓		✓		✓		✓		✓		✓		✓		✓	
CZ FE	✓		✓		✓		✓		✓		✓		✓		✓	
Firm $\times$ Time FE		✓		✓		✓		✓		✓		✓		✓		✓
CZ $\times$ Time FE		✓		✓		✓		✓		✓		✓		✓		✓
No. Firms	355,254	199,839	355,254	199,839	355,254	199,839	355,254	199,839	355,254	199,839	355,254	199,839	355,254	199,839	355,254	199,839

This table reports results for different horizons, H, for the following regressions: $\sum_{k=0}^{H}$ Log Vacancies$_{i,c,t+h} = \alpha_H + \beta_H$ MP easing$_t \times$ LMP$_{i,c,t-1} + \theta_H X_{i,c,t} + \gamma_{i,t+H} + \gamma_{c,t+H} + \varepsilon_{i,c,t+H}$, 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 easing$_t$ is the negative of the monetary policy shock by Jarociński and Karadi (2020), in which a positive value reflects monetary policy easing. LMP$_{i,c,t-1}$ is defined as the cumulative vacancy 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.