

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.

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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 ([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* has played an important role in the transmission of monetary policy to labor demand and wage growth that can explain these patterns. U.S. firms are well known to have significant labor market power, allowing them to “mark-down” their 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. This is because workers value earnings conditional on having a job but also value a higher probability of finding a job. In this environment, firms with labor market power can raise wages less in response to a positive demand shock, and instead, post more vacancies and hire more. This outcome relies on labor market power being associated with either more efficient job matching, e.g. due to vacancies from high market power firms being more visible, or lower costs of posting vacancies, e.g. due to fixed costs of recruiting and size effects.

To test the predictions of the model, we employ the near universe of online job postings provided by Burning Glass Technologies (BGT) to study how the transmission of monetary

policy is affected by the presence of labor market power. In what follows, we relate vacancies to labor demand. BGT data cover 250 million online job vacancy postings, and include information on the firm, location, posted date, job requirements, and offered wage, among other details. The highly disaggregated data allow us to construct firm-region specific market 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 follows the workhorse model of Cournot competition in which market power can be expressed as the market share for each firm.¹ 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.

As predicted by our model, we show that firms that have a larger market share pay significantly lower wages even conditional on a battery of job characteristics, such as the occupation and requirements for education, software, experience, etc. This negative correlation between market share and wages provides assurance that the market share indeed reflects market power (in the form of a markdown) and mitigates the concern that higher market 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 (such as financial constraints or product market power) unrelated to labor market power. Quantitatively, a firm at the 50th percentile of labor market power increases its labor demand by $\approx 7\%$ in response to a 10 basis point surprise monetary loosening while a firm at the 95th percentile of the labor market power distribution increases labor demand by $\approx 9\%$. Moreover, the effect of monetary policy shocks on firms with market power is much more persistent, with effects economically large and statistically significant at least for eight quarters. A simple back-of-the-envelope calculation attributes about one-quarter of the cumulative response of vacancies to monetary policy shocks after four quarters to labor market power. This calculation compares the response of vacancies using the observed labor market power in the data to a scenario where we equalize labor market power to zero for each of the firms.

Moreover, these effects of labor market power are more pronounced for vacancies with

¹See [Atkeson and Burstein \(2008\)](#).

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, with the relative response of wages not depending 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, with a flat 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; Coglianesi 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 the 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 \(2020\)](#), [Baqae 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 [Baqae 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 vacancies respond more to shocks than wages for firms with labor market power.

Consider a stylized economy where firms can post wages (w) and vacancies (v) in separate labor markets. Hiring is represented by a function $h = h(w, v; HH) = \phi\left(\frac{v}{u}\right)u$, where the probability of a worker finding a job is $\phi\left(\frac{v}{u}\right)$ and $\frac{v}{u}$ denotes market tightness, or the ratio of vacancies v and unemployment u . 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 .²

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 firms' 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.

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

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

²This 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.

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 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 if we assume there is no effect of monetary policy on households' labor supply.

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

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

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

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

We choose to model labor market power as resulting in lower marginal costs of hiring. Other papers have developed models in which more labor market power reduces the elasticity of labor supply, as firms with labor market power are harder to substitute away from. In the search and matching framework developed by [Jarosch et al. \(2019\)](#), the fact that the firm has a larger market share increases the probability of a single worker coming across the same firm in the future. This gives the firms with larger shares more control over the worker's outside option and allows for a stronger bargaining position, which results in lower wages. We intend to extend our model to such considerations in future versions of the 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 ≈ 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 basic wage.

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); 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.

4 Measuring Labor Market Power in BGT

4.1 Definition of Labor Market Power (LMP)

For our baseline results, 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. Using a firm’s market share of vacancies as a proxy for market power is justified theoretically, for instance in oligopsonistic settings or in search and matching models as discussed in the Literature sub-section of the Introduction.

We define a local labor market as a U.S. census commuting zone. This breakdown is very fine with some of the smaller firms not having two subsequent periods of posting the same vacancies. To avoid losing too many observations when computing the share of vacancies posted, we use the cumulative vacancies up to any given date, defined as:

$$\text{Market Share}_{i,c,t} = \frac{\sum_{\tau \leq t} v_{i,c,\tau}}{\sum_{\tau \leq t} \sum_i v_{i,c,\tau}} \quad (2)$$

where vacancies in commuting zone c , for firm i at time τ are denoted by $v_{c,i,\tau}$. An additional advantage of this measure 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. Market shares are highly skewed, with most firms having close to zero market share and a small number of firms having substantial labor market power. [Figure 2](#) plots the distribution of labor market power as measured in [Equation 2](#). The left-hand side plots the distribution of market shares across firms. The right-hand side plots the distribution of the 95th percentile market share across commuting zones. The average vacancy is exposed to a market share of 0.8%, a median of 0.1%, and the 95th percentile is 3.7%. 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).

Theoretically, higher labor market power should correspond to lower wages in the cross-section. [Figure 3](#) plots the average wage a firm posts on its vacancies for a particular commuting zone on the y-axis against the labor market share of that same firm in the commuting zone on the x-axis. To account for the right-skewed nature of the labor market share, the x-axis is on a log-scale. The left panel plots the relationship for non-college vacancies and the right panel for college vacancies. A large portion of the distribution of

labor market shares offers similar posted wages. In particular, firms that have a market 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 group differences are not meaningful. Even the firm that has a market 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 that has a market share of 0.1%, posting 1 in every 1000 vacancies, posts an average wage of less than US\$45,000 for non-college vacancies.

The same pattern is visible for college vacancies, with posted wages declining more linearly than for non-college vacancies, but with a large drop in posted wages beyond a 0.005% market share. As expected, the overall level of wages posted is significantly higher at around US\$76,000 for firms with a market share of < 0.00005) and around US\$70,000 for firms with a market share of > 0.001 .

The negative relationship between labor market shares and wages could suffer from a spurious correlation and compositional biases. For instance, if firms with 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 the 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 battery of vacancy characteristics and find that even after controlling for observed and unobserved vacancy, firm, and region characteristics, firms with higher labor market shares post lower wages on their vacancies ([Table 2](#)). We interpret this evidence as a signal that our measure of labor market power is a good proxy for actual labor market power.

We also compute the Herfindahl-Hirschman index (HHI) at the commuting zone level as an 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:

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

where the market share is calculated as described in [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 examine where the firms with significant labor market power are located and which sectors they operate in. For instance, we explore whether they are high-productivity superstar firms, or smaller firms that dominate smaller local labor markets.

To tackle these questions, we examine the characteristics of regions that host firms with high labor market power. Regions with a high labor market power firm 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 show up as having a high 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 market power measures on a map of the U.S. ([Figure 4](#)). Note that the regions with most 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 firm and industry perspectives. We find that top labor market power firms are as likely to hire college educated worker, but are slightly more likely to require specific software skills ([Table 4](#)). The sectors where firms with high market power are prevalent include educational services, health care, retail trade, accomodation and food services and mining ([Figure 6](#)). Moreover, high market power firms are more likely to be in tradable sectors with 47% of top LMP firms in tradable sectors versus 36% of non-top LMP firms. Looking at the distributions of vacancy shares in the different sectors (see [Figure 5](#)), we again notice a significant difference across sectors: the dispersion of labor market power seems to be much larger for health care, educational services and manufacturing.

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, there is significant heterogeneity across vacancy types — vacancies that do not require a college degree or tech skills react more to monetary policy in the presence of labor market power.

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:

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

where LMP denotes labor market power as measured by the vacancy market share defined in Equation 2, $X_{i,c,t}$ includes the Federal Reserve information shock and its interactions with labor market share, $\gamma_{i,t}$ are firm-time fixed effects that absorb any firm-time variation like productivity, improved funding conditions, or changes in stock prices, as well as product market power which is often defined at the firm-level, $\gamma_{c,t}$ are commuting zone - time effects that absorb any time-varying regional shocks, such as local demand shocks.

Vacancies of firms with labor market power are more responsive to monetary policy shocks (see Table 5). 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 negative and statistically significant. The coefficient of -0.348 indicates that for a firm without labor market power, vacancy postings fall by 3.48% in response to a 10 basis points contractionary monetary policy shock. The interaction between the monetary policy shock and lagged market share is also negative and statistically significant. The negative interaction term reflects that labor market power amplifies the response of monetary policy shocks, i.e. firms that have a larger market share in a commuting zone reduce their vacancy postings by even more compared to a firm that has no labor market power. In column 2 we include firm fixed effects to 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 negative 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 the average income per capita during our sample period. The inclusion of commuting fixed effects leaves the results unchanged. Column 5 introduces firm, time, and commuting zone fixed effects simultaneously.

The introduction of firm-times 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 resulting 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.³ 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 labor market 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 than 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% labor market share is very rare.

The results are also illustrated in [Figure 7](#) with numerical examples. We use column 4 of [Table 5](#) 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

³For 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.

three hypothetical firms at the 5th, 50th, and 95th percentile of the labor market share distribution. For firms at the 5th and 50th percentile of the distribution, the response of the change in vacancy postings is virtually the same at around 7%. The number is consistent with column 4 of [Table 5](#). 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 95th 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.

We check robustness of this specification to various monetary policy shocks. Please refer to [Table A2](#) for estimation results.

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:

$$\sum_{h=0}^H \text{Log Vacancies}_{i,c,t+h} = \alpha + \beta_h \text{MP shock}_t \times \text{LMP}_{i,c,t-1} + \theta_h X_{i,c,t} + \gamma_{i,t+h} + \gamma_{c,t+h} + \varepsilon_{i,c,t+h}$$

where h is a given horizon of vacancy postings. [Figure 10](#) 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. [Figure 9](#) explicitly compares the response of labor demand over time for the median firm in terms of labor market power to a firm with a high degree of labor market power (95th percentile). Both firms increase their labor demand strongly, peaking at one quarter after the surprise. The firm with a large degree of labor market power increases its demand by around 3% in response to a 10 basis point monetary policy loosening, while a firm with median labor market power increases its vacancy postings by only 2%. After the first quarter, both firms decrease their vacancy postings. However, for the firm with medium labor market power, the effect of monetary policy seems to be purely temporary, with the additional number of vacancy postings reaching close to zero after four quarters. In contrast, the firm with significant labor market power has still posted more vacancies over the four quarters after the shock compared to a scenario in which monetary policy would not have been active, suggesting that monetary policy

shocks have persistent effects for firms with labor market power.

We check robustness to the alternative industry-level labor market power definition. Please refer to [Table A1](#) and [Figure A2](#) for results.

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 Burning glass 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:

$$\begin{aligned} \text{Log Vacancies}_{i,c,t,j} = & \alpha + \beta \text{MP shock}_t \times \text{Labor Market Power}_{i,c,t-1} + \\ & \delta \text{MP shock}_t \times \text{Labor Market Power}_{i,c,t-1} \times \text{Type}_j + X_{i,c,t} \\ & + \gamma_{i,t} + \gamma_{c,t} + \varepsilon_{i,c,t} \end{aligned} \quad (4)$$

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 δ 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 (δ), that would mean that the effect is weaker for $[\text{Type} = 1]$.

[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 (see [Figure 11](#)).

Column 2 illustrates whether this effect is partly driven by labor market power. Indeed, the interaction between the monetary policy shock, market share and the vacancy type dummy is positive and statistically significant. The positive triple interaction term shows

that labor demand effects of labor market power in response to a monetary policy shock are stronger for non-college vacancies. When interpreting the economic magnitude, we can see that the effect is around -7.8 for non-college vacancies and $(-7.8 + 2.9) = -4.9$ for college vacancies. The results are similar for software-related vacancies. In column 3 we can see that software vacancies are less responsive to monetary policy in general, and when firms exhibit labor market power their adjustment seems to be done along the non-software dimension, rather than on the more tech-related vacancies.

Our specification is based on symmetric effects of positive and negative monetary policy surprises.⁴ 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. We therefore merge our BGT data with Compustat data for a large number of publicly traded firms to analyze the relationship between vacancy postings and employment growth. We aggregate vacancy postings to the firm-year level and fuzzy merge the BGT firm name to Compustat.⁵ First, we execute a standard string cleaning procedure, removing excessive white spaces and company's business structure, 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 8231 firm matches from 14,983 firms in Compustat in the years between 2008 to 2019, of which 3,217 are exact matches, and

⁴We 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

⁵The quarterly version of Compustat does not have employment information, which is why we use the annual Compustat file.

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 estimate the following regression equation:

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

where $\Delta Employment_{i,t}$ is the log change in employment of firm i between year t and $t - 1$ in Compustat.⁶ $\text{Log Vacancies}_{i,t}$ is the log number of vacancies posted by firm i in year t from BGT. $\text{Log Vacancies}_{i,t}$ 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 12](#) 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 ($\text{Log Vacancies}_{i,t} = 1$) is associated with a 0.74 percentage point stronger employment growth.

[Figure 9](#) shows that after four quarters, a firm with high labor market power increased its vacancy postings by a factor of 2 in response to a 100 basis point accommodative monetary policy shock. A firm with medium labor market power instead did not increase 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, monopolists 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

⁶The 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).

hiring and employment growth. Even for firm with a large degree of labor market power there is a strong relationship between vacancy postings and employment growth ⁷

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. 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:

$$\sum_{h=0}^H \text{Posted Wage}_{i,c,t+h} = \alpha + \beta_h \text{MP shock}_t \times \text{LMP}_{i,c,t-1} + \theta_h X_{i,c,t} + \gamma_{i,t+h} + \gamma_{c,t+h} + \varepsilon_{i,c,t+h}$$

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 range for the wage offered. When a range is reported we take the average between the min and the max.⁸ We find that, as expected, an accommodative monetary policy shock increases posted wages, but that the response of posted wages to the monetary policy shock is not significantly different for firms with or without labor market power (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) (Table 7).

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. Figure 1 shows that the wage Phillips curve has flattened significantly and was particularly flat during the period between the GFC and the Covid-19 crisis. The lower estimated negative

⁷The positive relationship is robust to using other specifications, such as log-log equations.

⁸Hazell et al. (2021) suggests that employers pay the posted wages, and that smaller firms tend to post wages.

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:

$$\text{Wage Growth}_{c,t} = \alpha + \beta_1 \text{Unemployment Rate}_{c,t} + \beta_2 \mathbb{1}\text{Labor Market Power}_{c,t} + \beta \text{Unemployment Rate}_{c,t} \times \mathbb{1}\text{Labor Market Power}_{c,t} + \epsilon_{c,t} \quad (6)$$

where $\text{Wage Growth}_{c,t}$ 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, $\mathbb{1}\text{Labor Market Power}_{c,t}$, 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. \(2020\)](#). $\text{Unemployment Rate}_{c,t}$ is the unemployment rate from BLS at the commuting zone year-level.

[Figure 13](#) 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 8](#), 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 the labor market. We find striking evidence that labor market power strengthens the effect of monetary policy on labor demand. Empirically, our results show that a firm with more labor market power in a certain region expands its vacancy postings by about 30% more relative to its counterparts. 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, due to either 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 soften 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, if 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 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 number 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)
Market Share _{i,c,t}	-0.360*** (-3.85)	-0.193** (-2.44)	-0.168*** (-2.83)	-0.174** (-2.31)	-0.181*** (-2.81)
College _{v,i,c,t}	0.238*** (41.46)	0.236*** (31.56)	0.173*** (36.31)	0.170*** (37.33)	0.162*** (40.28)
Software Skills _{v,i,c,t}	0.028*** (8.13)	0.028*** (7.01)	0.015*** (4.25)	0.015*** (4.34)	0.013*** (4.51)
Specialized _{v,i,c,t}	0.088*** (29.65)	0.077*** (23.80)	0.056*** (21.47)	0.057*** (23.04)	0.054*** (24.33)
Routine Manual _{v,i,c,t}	-0.110*** (-18.83)	-0.105*** (-15.99)	0.037*** (3.36)	0.037*** (3.44)	0.049*** (4.50)
Routine Cognitive _{v,i,c,t}	-0.144*** (-28.15)	-0.132*** (-22.18)	0.054*** (5.16)	0.056*** (5.72)	0.071*** (7.01)
Non-Routine Manual Physical _{v,i,c,t}	-0.058*** (-9.42)	-0.057*** (-8.36)	0.036*** (3.18)	0.040*** (3.60)	0.033*** (3.51)
Non-Routine Manual Inter-Personal _{v,i,c,t}	0.044*** (10.32)	0.044*** (9.31)	0.038*** (3.87)	0.037*** (3.89)	0.042*** (3.99)
Non-Routine Cognitive Analytical _{v,i,c,t}	0.064*** (12.20)	0.057*** (9.83)	0.103*** (12.89)	0.106*** (13.88)	0.102*** (12.66)
Non-Routine Cognitive Personal _{v,i,c,t}	0.159*** (33.75)	0.158*** (28.52)	0.040*** (7.02)	0.041*** (7.73)	0.040*** (8.10)
Constant	10.580*** (2440.79)	10.607*** (2126.31)	10.613*** (1249.29)	10.612*** (1300.34)	10.615*** (1292.89)
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	173057	144813	141764	141715	141708

This table reports results for the following vacancy-level regression: $\text{Log wages}_{v,i,c,t} = \alpha + \beta \text{Labor Market Power}_{i,c,t} + \theta X_{v,i,c,t} + \gamma_{i,t} + \gamma_{c,t} + \gamma_{ind,t} + \varepsilon_{v,i,c,t}$, where $\text{Log wages}_{v,i,c,t}$ is defined as the log of posted wage in vacancy v for firm i , in commuting zone c in quarter t . $\text{Labor Market Power}_{i,c,t}$ is defined as the cumulative labor market 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 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 top firms within those regions

	HHI (1)	GDP per Capita (2)	House Prices (3)	Labor Force (4)	Tightness (5)	Unemployment Rate (6)
Top Firm Present	0.071*** (0.004)	-0.131*** (0.045)	-0.047 (0.081)	-0.451*** (0.056)	-0.068*** (0.012)	0.000 (0.001)
Obs.	29,315	26,283	23,122	29,277	29,277	29,277

This table reports the results of the following regression: $y_{rt} = \alpha + \beta[\text{Top Firm is Present in the Region}]_{rt} + \varepsilon_{rt}$. Regression is using the collapsed panel data at the region-time level. Top firm is defined as the firm-region-level establishment that belongs to the top 5% of the vacancy share establishments across all regions. A region is defined as having a top firm if there is a top firm in this region. 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: Vacancy Characteristics for Top Firms

	Share College Vacancies			Share Software Vacancies		
	(1)	(2)	(3)	(4)	(5)	(6)
top	0.024 (0.027)	0.011 (0.013)	0.011 (0.011)	-0.113*** (0.014)	0.053*** (0.009)	0.052*** (0.009)
Obs.	15,810,352	12,422,252	12,422,203	15,810,352	12,422,252	12,422,203
CZ FE		✓	✓		✓	✓
NAICS3 FE		✓			✓	
time FE		✓			✓	
NAICS3*time FE			✓			✓

This table reports the results of the following regression: $Y_{irt} = \alpha + \beta[\text{Firm is Top}]_{irt} + \gamma + \varepsilon_{irt}$. Regression is using panel data at the firm-region-time level. Top firm is defined as the firm-region-level establishment that belongs to the top 5% of the vacancy share establishments across all regions. The dependent variable is the share of vacancies that require a college degree among all the vacancies posted by the firm and the share of vacancies that require software skills among all vacancies posted by the firm. Different regressions use different sets of fixed effects noted at the bottom of the table. Standard errors are reported in the parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Labor Demand Effect of Monetary Policy

	Log Vacancies _{<i>i,c,t</i>}						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MP Shock _{<i>t</i>}	-0.351*** (0.036)	-0.647*** (0.032)		-0.696*** (0.035)			
Market Share _{<i>i,c,t-1</i>}	23.166*** (1.816)	14.505*** (1.252)	14.958*** (1.275)	20.318*** (1.534)	20.866*** (1.560)	21.439*** (1.667)	22.713*** (1.639)
MP Shock _{<i>t</i>} × Market Share _{<i>i,c,t-1</i>}	-13.913*** (3.111)	-3.400* (1.789)	-5.439*** (1.834)	-5.442** (2.330)	-7.624*** (2.398)	-8.722** (3.389)	-7.895** (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	377669	355254	355254	355254	355254	199839	199839

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

Table 6: Labor Demand Effect of Monetary Policy across Vacancy Types

	Log Vacancies _{<i>i,c,t,j</i>}			
	(1)	(2)	(3)	(4)
Market Share _{<i>i,c,t-1</i>}	18.805*** (1.311)	19.173*** (1.337)	21.786*** (1.526)	21.736*** (1.523)
Type	-0.144*** (0.018)		-0.227*** (0.013)	
Market Share _{<i>i,c,t-1</i>} × Type	-1.596*** (0.565)	-2.286*** (0.575)	-8.168*** (0.718)	-7.932*** (0.712)
MP Shock _{<i>t</i>} × Market Share _{<i>i,c,t-1</i>}	-7.213*** (2.785)	-7.785*** (2.843)	-8.564** (3.633)	-8.701** (3.631)
MP Shock _{<i>t</i>} × Type	0.412*** (0.041)		0.147*** (0.040)	
MP Shock _{<i>t</i>} × Market Share _{<i>i,c,t-1</i>} × Type	1.753 (1.652)	2.938* (1.623)	2.756 (2.401)	3.576 (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 results for the following regression: $\text{Log Vacancies}_{i,c,t,j} = \alpha + \beta \text{MP shock}_t \times \text{Labor Market Power}_{i,c,t-1} + \delta \text{MP shock}_t \times \text{Labor Market Power}_{i,c,t-1} \times \text{Type}_j + X_{i,c,t} + \gamma_{i,t} + \gamma_{c,t} + \varepsilon_{i,c,t}$, where $\text{Log Vacancies}_{i,c,t}$ is defined as the log number of vacancies posted by firm i , in commuting zone c in quarter t . MP shock_t is the monetary policy shock by [Jarociński and Karadi \(2020\)](#), in which a positive value reflects monetary policy tightening. $\text{Labor Market Power}_{i,c,t-1}$ is defined as the cumulative labor market share of firm i in commuting zone c at quarter $t-1$. Type_j is a dummy taken the value of one if the vacancy requires a college degree/software skills and zero if the the vacancy does not require a college degree/software skills. For more details see [section 3](#). $\gamma_{i,t}$ are firm-time, $\gamma_{c,t}$ are commuting-zone(CZ)-time fixed effects. Standard errors are double clustered at the firm and commuting zone level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Wage Effect of Monetary Policy

	$\Delta \text{Log Wages}_{i,c,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
MP Shock _{<i>t</i>}	-0.001 (0.036)	-0.146*** (0.021)				
Market Share _{<i>i,c,t-1</i>}	0.277** (0.138)	-0.084 (0.086)	-0.011 (0.093)	0.112* (0.065)	0.354*** (0.077)	0.390*** (0.081)
MP Shock _{<i>t</i>} × Market Share _{<i>i,c,t-1</i>}	-0.192 (0.389)	0.579** (0.269)	-0.009 (0.271)	-0.090 (0.277)	-0.433 (0.349)	-0.363 (0.482)
Obs.	3,611,431	3,546,366	3,546,366	3,546,366	2,716,562	2,715,673
Firm FE		✓	✓	✓		
Time FE			✓	✓		
CZ FE				✓	✓	
Firm*Time FE					✓	✓
CZ*Time FE						✓
No. Firms	281380	216315	216315	216315	97858	97856

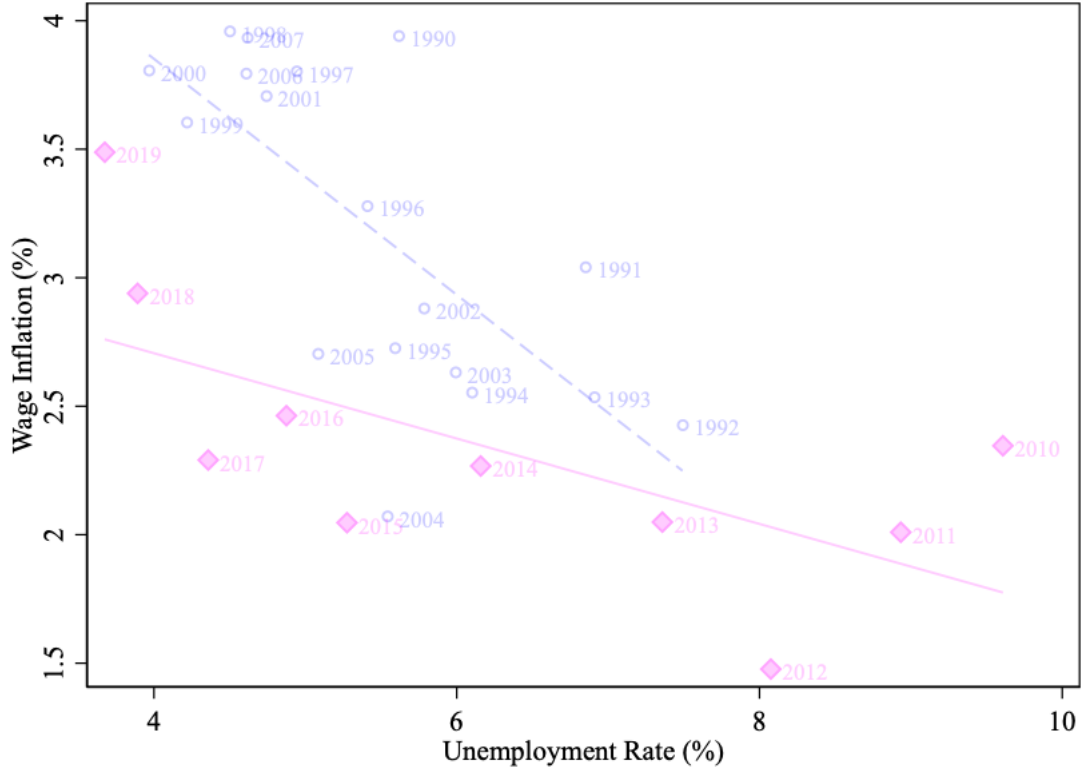
This table reports results for the following regression: $\text{Log Wage}_{i,c,t} = \alpha + \beta \text{MP shock}_t \times \text{Labor Market Power}_{i,c,t-1} + X_{i,c,t} + \gamma_{i,t} + \gamma_{c,t} + \varepsilon_{i,c,t}$, where $\text{Log Wage}_{i,c,t}$ is defined as the log wage of vacancies posted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

Table 8: Wage Phillips Curve by Labor Market Power

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

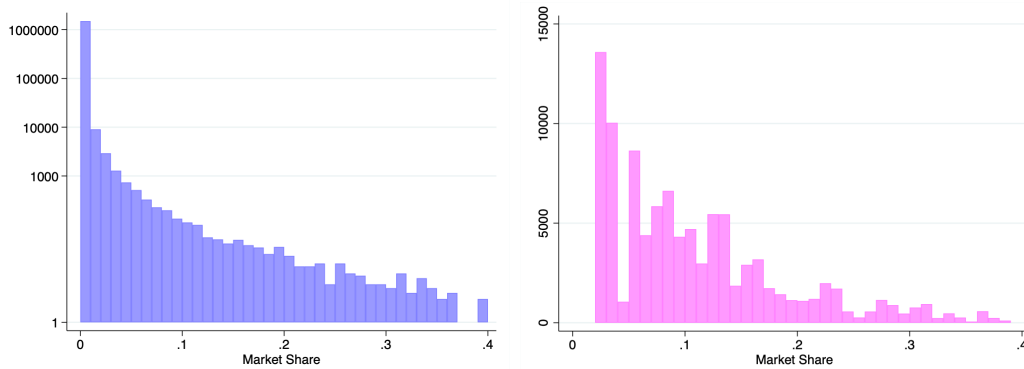
This table reports results for the following regression: $\text{Wage Growth}_{c,t} = \alpha + \beta_1 \text{Unemployment Rate}_{c,t} + \beta_2 \mathbb{1}\text{Labor Market Power}_{c,t} + \beta \text{Unemployment Rate}_{c,t} \times \mathbb{1}\text{Labor Market Power}_{c,t} + \epsilon_{c,t}$ where $\text{Wage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

Figure 1: Wage Phillips Curve



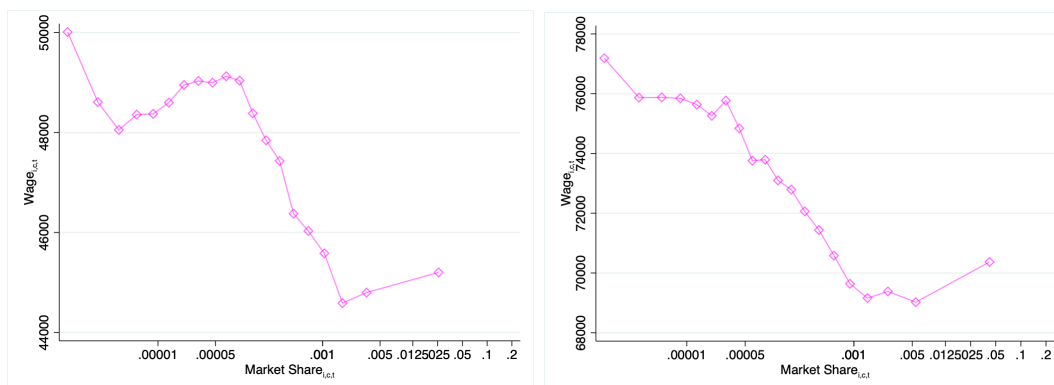
This figure plots wage growth against the unemployment rate. The pink diamonds are for the years 2010-2019 and the pink solid line the linear fit. The blue hollow dots are for the years 1990-2007 and the blue dashed line the linear fit. The wage inflation is defined as the log change in average hourly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

Figure 2: Distribution of Labor Market Share



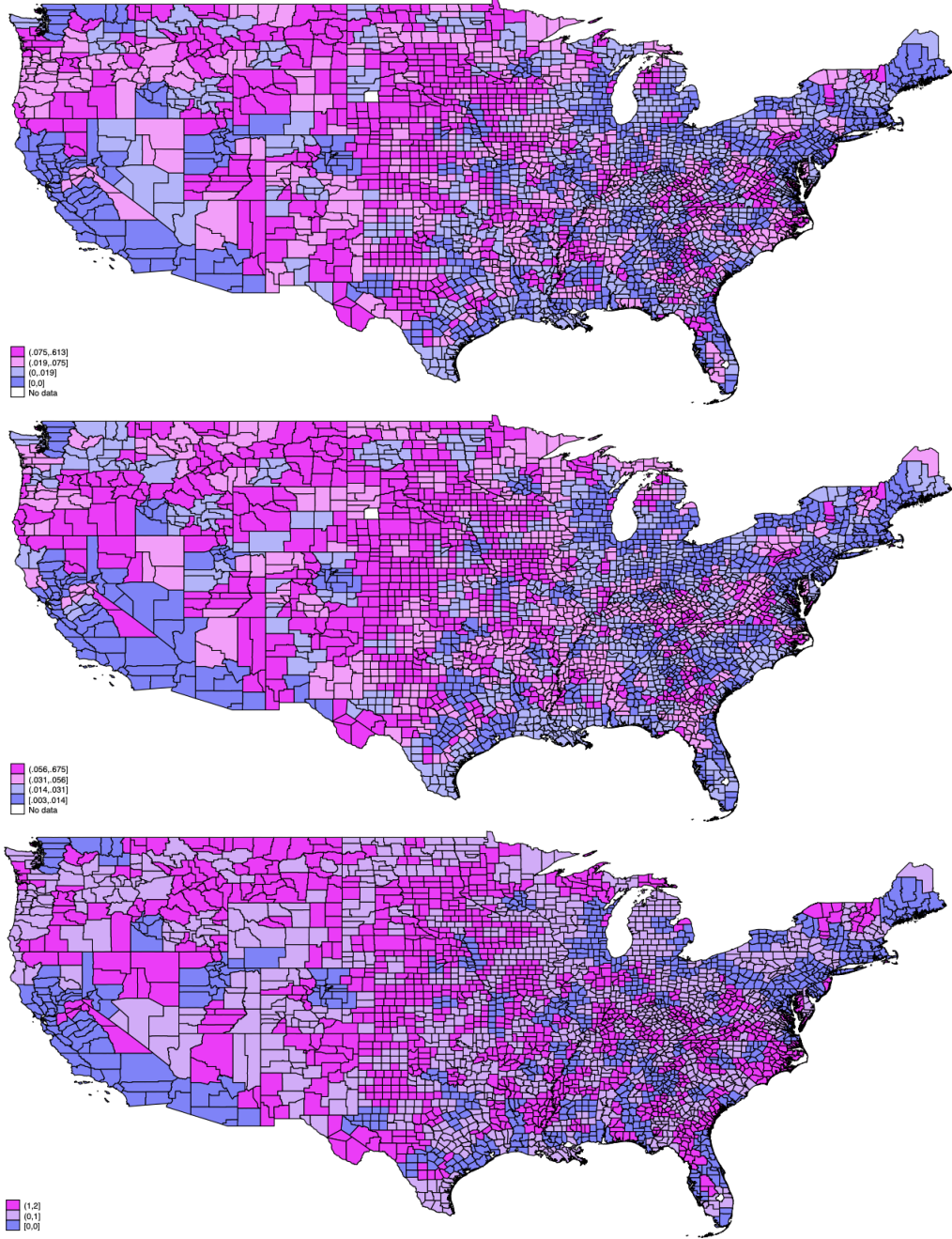
The left panel plots the histogram of the firm-commuting zone level market share defined as $\text{Market Share}_{i,c,t} = \frac{\sum_{\tau \leq t} v_{i,c,\tau}}{\sum_{\tau \leq t} \sum_i v_{i,c,\tau}}$ for each firm i in commuting zone c in quarter t . The y-axis scale is in logs. The right panel plots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

Figure 3: Labor Market Share and Wages



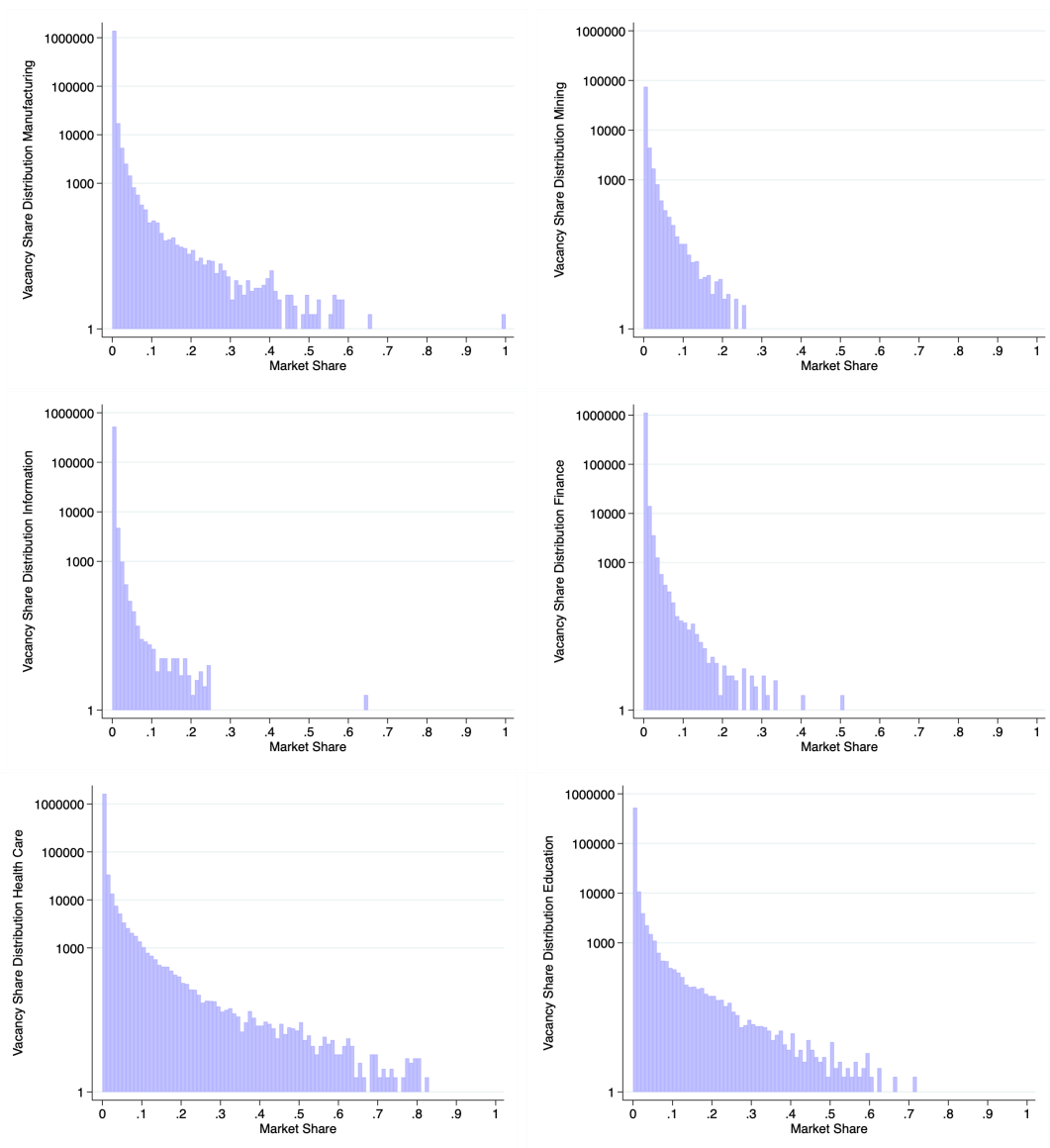
This figure plots a local polynomial smooth of wages on market share for non-college (left panel) and college (right panel) vacancies. The wages are defined as the average wage posted by firm i in commuting zone c in quarter t . The market share defined as $\text{Market Share}_{i,c,t} = \frac{\sum_{\tau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

Figure 4: Geography of Labor Market Power



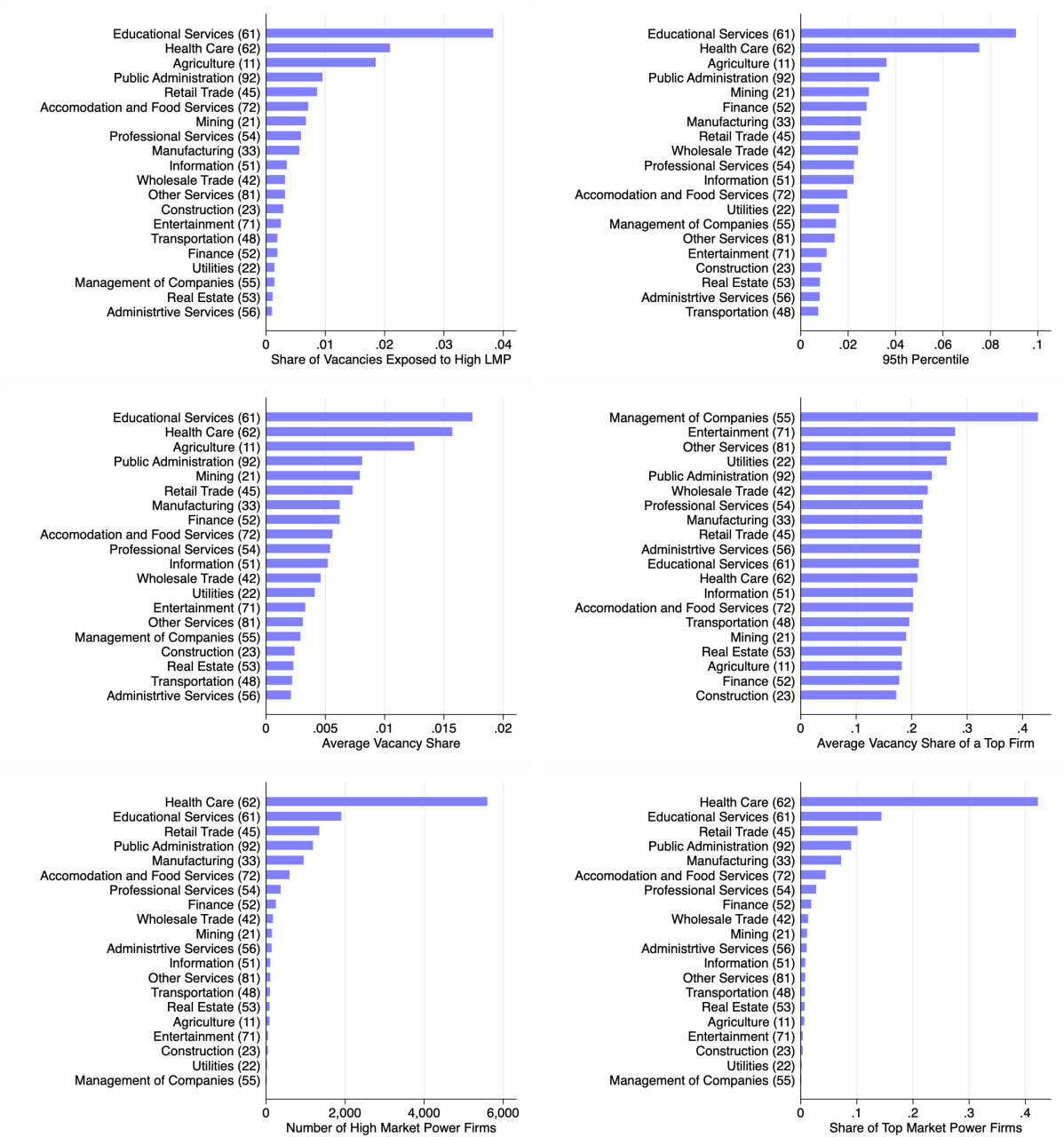
The figure reports different measures of Labor Market Power across the regions. Top firm is defined as the firm-region-level establishment that belongs to the top 5% of the vacancy share establishments across all regions. **Top panel** reports the average cross time share of vacancies controlled by the top firms. **Middle panel** reports the Herfindahl-Hirschman concentration index across regions. HHI is defined as a sum of squared vacancy shares across all firms within the regions. **Bottom panel** reports the number of top firms across regions with the highest bracket indicating that a region has more than 1 Top firm.

Figure 5: Distribution of Labor Market Share, Specific Industries



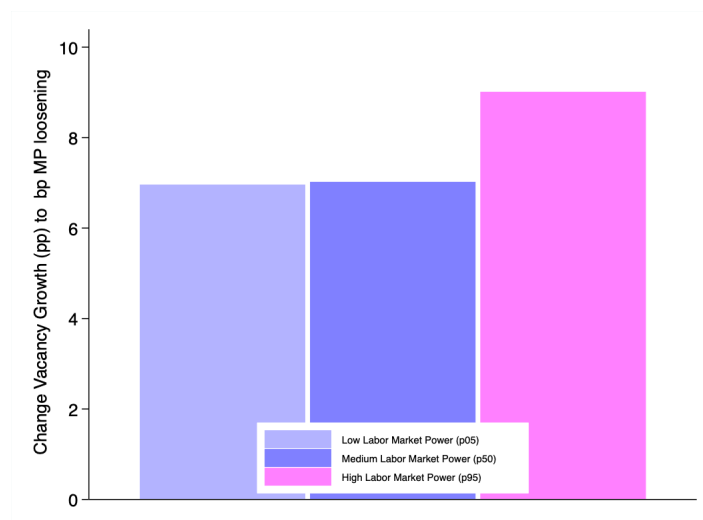
The figure plots the histogram of the firm-commuting zone level market share defined as $\text{Market Share}_{i,c,t} = \frac{\sum_{\tau \leq t} v_{i,c,\tau}}{\sum_{\tau \leq t} \sum_i v_{i,c,\tau}}$ for each firm i in commuting zone c in quarter t working in a specific industry. The y-axis scale is in logs. The right panel plots the histogram of the 95th percentile of firm-level market share across commuting zones.

Figure 6: Top Firms by Sector



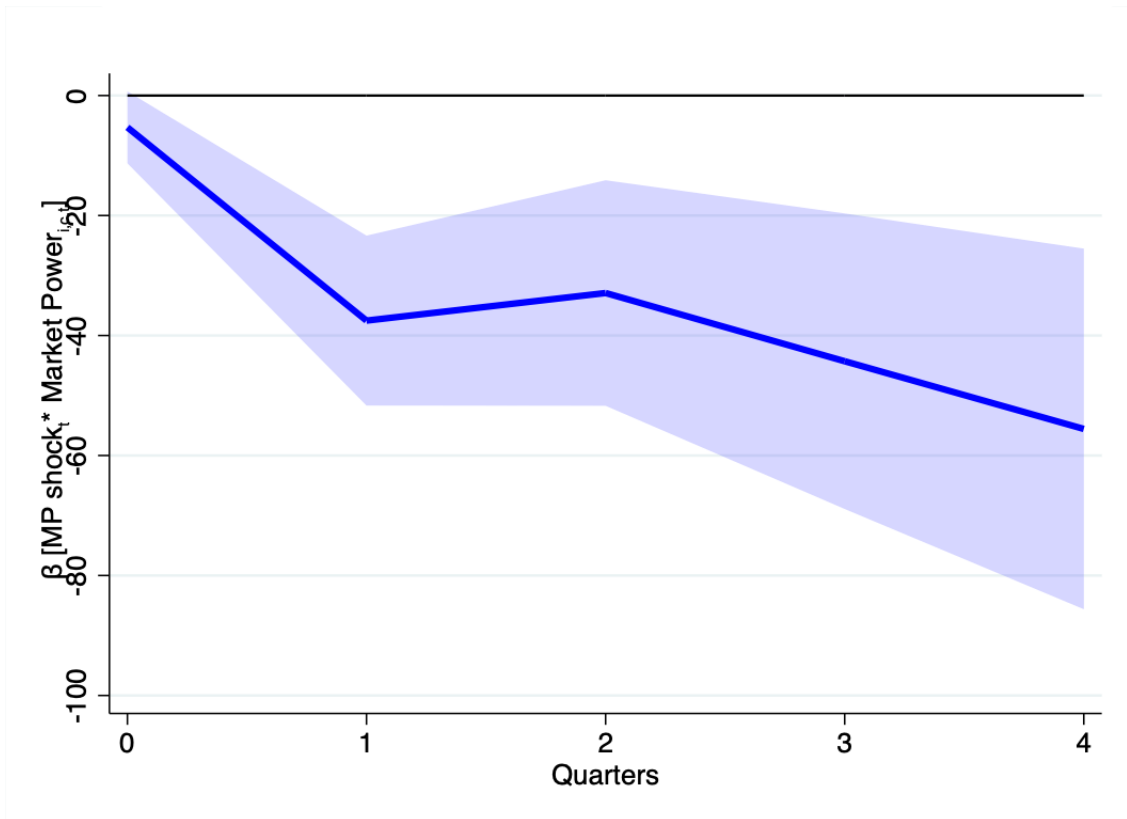
This figure plots different measures of Labor Market Power across industries. Top firm is defined as the firm-region-level establishment that belongs to the top 5% of the vacancy share establishments across all regions. High Labor Market Power is defined as a Labor Market Power of a Top firm. **Top Left panel** reports the share of vacancies exposed to top firms across the 2-digit NAICS industries. **Top Right panel** reports the vacancy share corresponding to the 95th percentile within each of the regions. **Middle Left panel** reports the average vacancy share of the firm-region establishments within each of the industries. **Middle Right panel** reports the average vacancy share of a Top firm within each of the industries. **Bottom Left panel** reports the number of Top firms within each of the industries. **Bottom Right panel** reports the share of Top firms belonging to each of the industries.

Figure 7: Change in Vacancy Postings in Response to Monetary Policy Accommodation



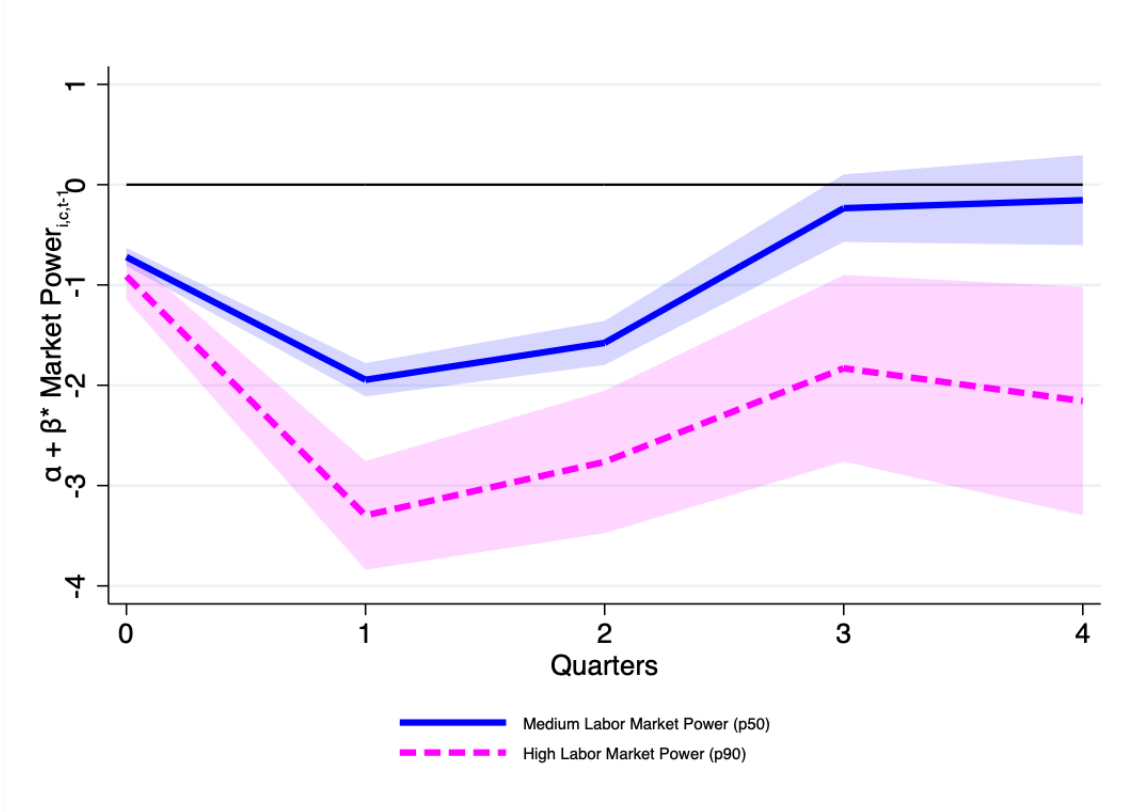
This figure plots the total effect of the accommodating monetary policy on vacancy postings given by: $\beta_{3,i}$ MP shock $_t \times$ Labor Market Power $_{i,c,t-1}$. Labor Market Power $_{i,c,t-1}$ is defined as the cumulative labor market share of firm i in the commuting zone c at quarter $t-1$.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

Figure 8: Dynamic Labor Market Power Effect on Vacancy Postings in Response to a Monetary Policy Tightening Shock



This figure plots β_h of $\sum_{h=0}^H \text{Log Vacancies}_{i,c,t+h} = \alpha + \beta_h \text{MP shock}_t \times \text{Labor Market Power}_{i,c,t-1} + \theta_h X_{i,c,t} + \gamma_{i,t+h} + \gamma_{c,t+h} + \varepsilon_{i,c,t+h}$ where $\text{Log Vacancies}_{i,c,t}$ is defined as the log number of vacancies posted by firm i , in commuting zone c in quarter t . MP shock_t is the monetary policy shock by [Jarociński and Karadi \(2020\)](#), in which a positive value reflects monetary policy tightening. $\text{Labor Market Power}_{i,c,t-1}$ is defined as the cumulative labor market share of firm i in commuting zone c at quarter $t-1$. For more details see [section 3](#). Standard errors are double clustered at the firm and commuting zone level. Shaded regions represent a 99% confidence interval.

Figure 9: Dynamic Response of Vacancy Postings to a Monetary Policy Tightening Shock

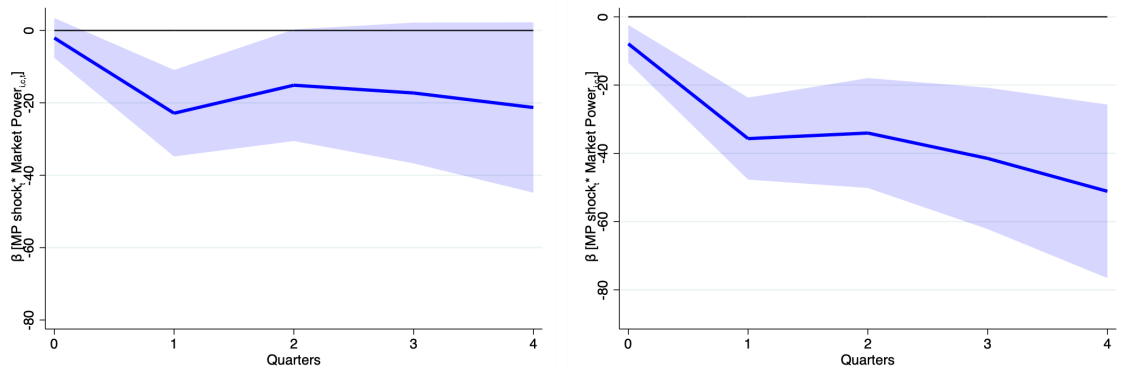


This figure plots the estimated response of vacancy postings for a firm a large extent of market power (95th percentile) in pink and medium market power (50th percentile) in blue from the following regression

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

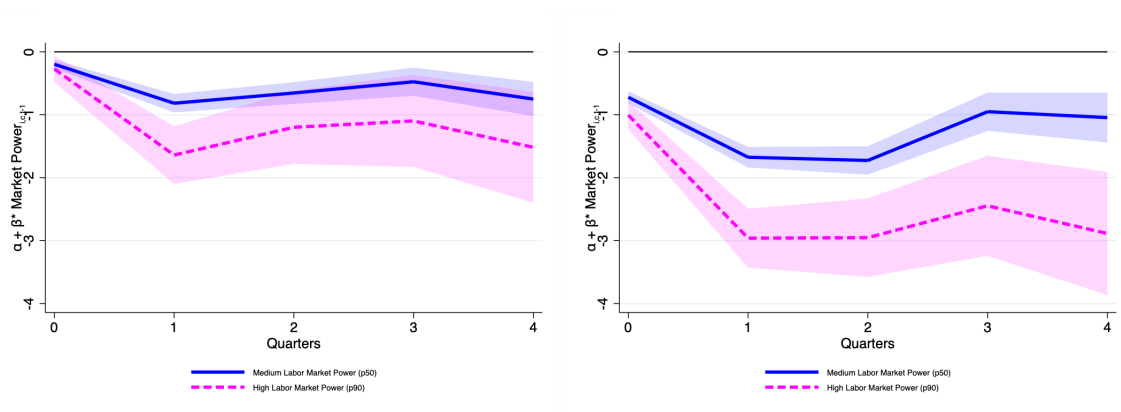
is defined as the log number of vacancies posted by firm i , in commuting zone c in quarter t . MP shock $_t$ is the monetary policy shock by [Jarociński and Karadi \(2020\)](#), in which a positive value reflects monetary policy tightening. Labor Market Power $_{i,c,t-1}$ is defined as the cumulative labor market share of firm i in commuting zone c at quarter $t-1$. For more details see [section 3](#). The pink lines is defined $\beta_1 + \beta^* \text{Labor Market Power}_{i,c,t-1}(P95)$ and the blue line is defined as $\beta_1 + \beta^* \text{Labor Market Power}_{i,c,t-1}(P50)$. Standard errors are double clustered at the firm and commuting zone level. Shaded regions represent a 99% confidence interval.

Figure 10: Dynamic Labor Market Power Effect on Vacancy Postings in Response to a Monetary Policy Tightening Shock



This figure plots β_h of $\sum_{h=0}^H \text{Log Vacancies}_{i,c,t+h} = \alpha + \beta_h \text{MP shock}_t \times \text{Labor Market Power}_{i,c,t-1} + \theta_h X_{i,c,t} + \gamma_{i,t+h} + \gamma_{c,t+h} + \varepsilon_{i,c,t+h}$ where $\text{Log Vacancies}_{i,c,t}$ is defined as the log number of vacancies posted by firm i , in commuting zone c in quarter t . **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 shock_t is the monetary policy shock by Jarociński and Karadi (2020), in which a positive value reflects monetary policy tightening. $\text{Labor Market Power}_{i,c,t-1}$ is defined as the cumulative labor market share of firm i in commuting zone c at quarter $t-1$. For more details see section 3. Standard errors are double clustered at the firm and commuting zone level. Shaded regions represent a 99% confidence interval.

Figure 11: Dynamic Response of Vacancy Postings to a Monetary Policy Tightening Shock Depending on Requirement of a College Degree

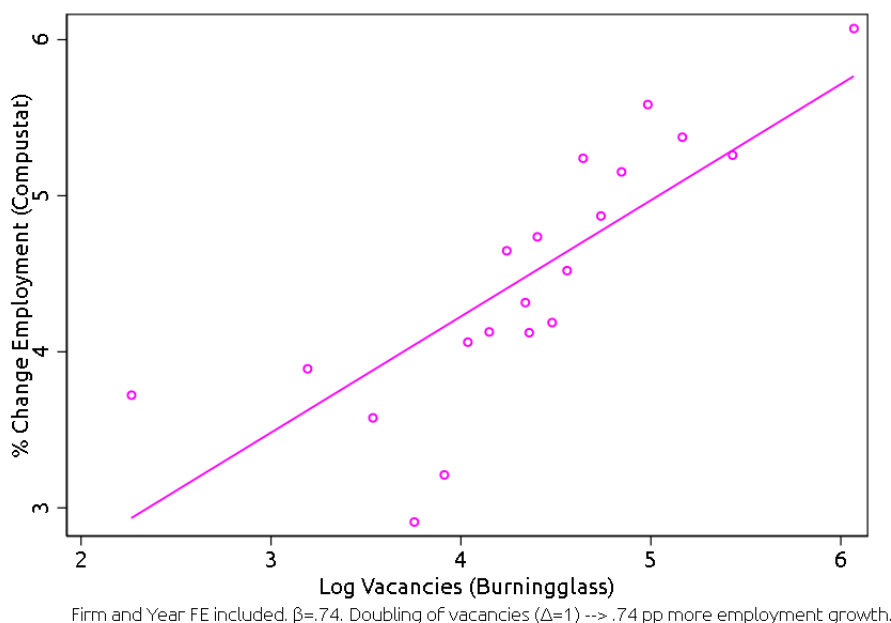


This figure plots the estimated response of vacancy postings for a firm a large extent of market power (95th percentile) in pink and medium market power (50th percentile) in blue from the following regression

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

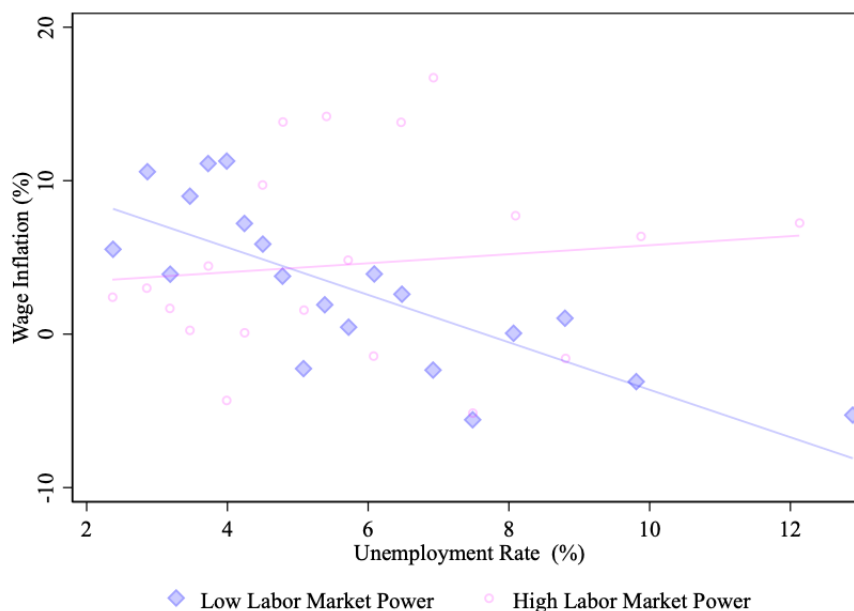
is defined as the log number of vacancies posted by firm i , in commuting zone c in quarter t . **The left panel** represents the response of the vacancies that require a college degree, **the right panel** represents vacancies that do *not* require a college degree. MP shock_t is the monetary policy shock by Jarociński and Karadi (2020), in which a positive value reflects monetary policy tightening. $\text{Labor Market Power}_{i,c,t-1}$ is defined as the cumulative labor market share of firm i in commuting zone c at quarter $t-1$. For more details see section 3. The pink lines is defined $\beta_1 + \beta^* \text{Labor Market Power}_{i,c,t-1}(P95)$ and the blue line is defined as $\beta_1 + \beta^* \text{Labor Market Power}_{i,c,t-1}(P50)$. Standard errors are double clustered at the firm and commuting zone level. Shaded regions represent a 99% confidence interval.

Figure 12: Sensitivity of Employment to Vacancy Postings



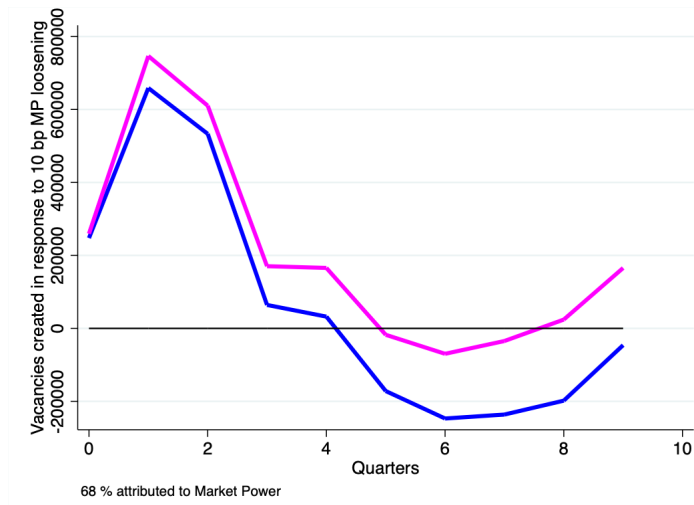
This figure plots a binscatterplot between the log change in employment from Compustat on Log Vacancy postings from BGT: $\Delta Employment_{i,t} = \alpha_i + \alpha_t + \beta_1 \text{Log Vacancies}_{i,t} + \epsilon_{i,t}$ where $\Delta Employment_{i,t}$ is the log change in employment of firm i between 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 13: Wage Phillips Curve by Labor Market Power



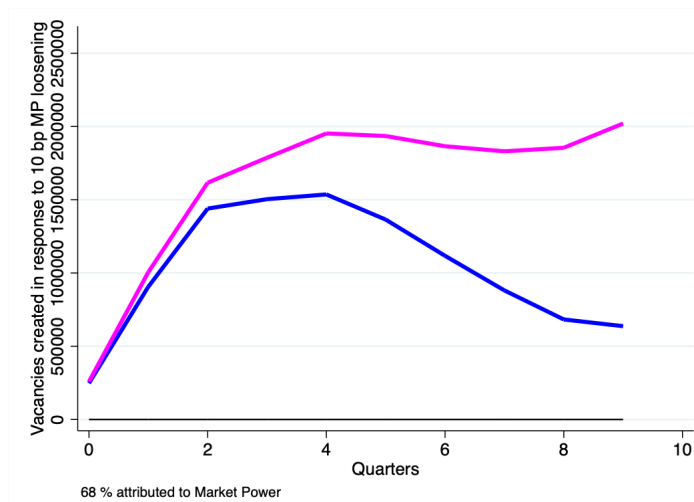
This figure plots a binscatter between wage growth and the unemployment rate on the commuting zone-year level. The y-axis refers to annual wage growth from Burning Glass Data vacancy postings. The x-axis measures the commuting zone unemployment rate based on BLS data. The blue (pink) diamonds (dots)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

Figure 14: Back-of-the-Envelope Calculation. Extra vacancies generated in the economies with and without labor market power



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

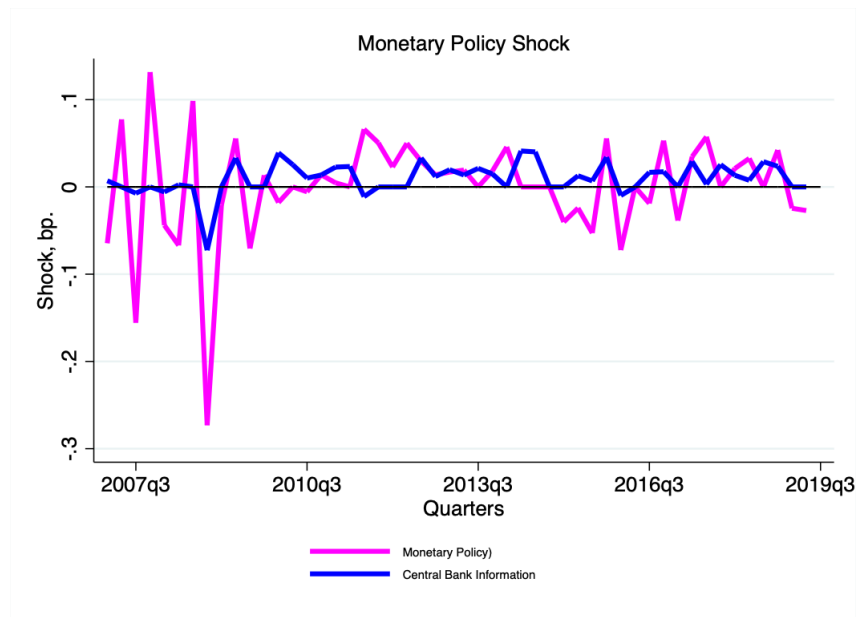
Figure 15: Back-of-the-Envelope Calculation. Extra vacancies are generated in the economies with and without labor market power. Cumulative effect



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

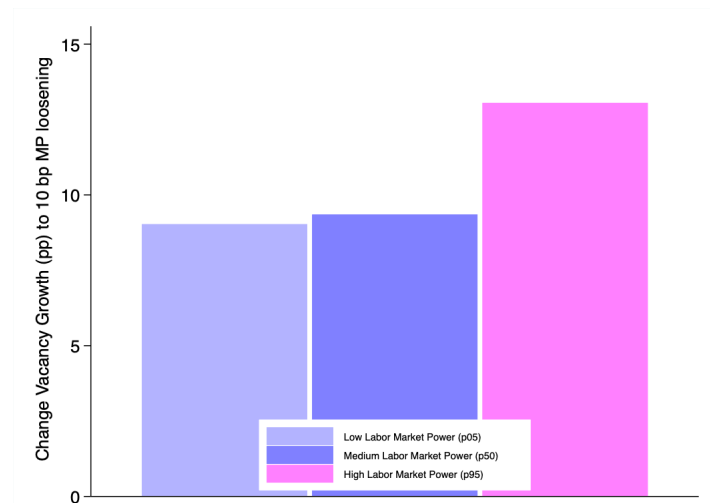
A Appendix Tables and Figures

Figure A1: Monetary Policy Shocks



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 tightening. The measure for the shock series is bp. 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: Change in Vacancy Postings in Response to Monetary Policy Accommodation



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

Table A1: Labor Demand Effect of Monetary Policy

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

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

Table A2: Robustness to the Choice of Monetary Policy Shock

	Log Vacancies _{<i>i,c,t</i>}					
	(1)	(2)	(3)	(4)	(5)	(6)
MP shock _{<i>t</i>} × Labor Market Power _{<i>i,c,t-1</i>} ^{alt}	-1.415*** (0.228)	-1.387*** (0.188)	0.693*** (0.112)	-2.942*** (0.250)	-0.849*** (0.102)	-1.430*** (0.174)
R-squared	0.467	0.468	0.468	0.468	0.468	0.468
Obs.	12,851,727	12,851,727	12,851,727	12,851,727	12,851,727	12,851,727
Firm*Time FE	✓	✓	✓	✓	✓	✓
CZ*Time FE	✓	✓	✓	✓	✓	✓
No. Firms	NS	BRW	J u1	J u2	J u3	J u4

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