What Does Monetary Policy Do To Different People?

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Abstract

Does monetary policy affect people differently depending on their education level, their marital status, their race or their gender? To study this question, we use a Vector Autoregression where monetary policy effects are identified via an instrument to study how labor market outcomes differ across these groups after a monetary policy shock. The response of the aggregate unemployment rate to a monetary policy shocks masks *massive* heterogeneity. We find that the magnitude of the response of the *difference* of unemployment rates across groups is often between 50 percent and 100 percent of the peak response of the *level* of the aggregate unemployment rate.

JEL Classification: E24, E50

Key Words: Monetary Policy, Heterogeneity

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" In fact, the distributional effects of monetary policy are complex and uncertain."
— Ben Bernanke (Bernanke (2015))

1 Introduction

One of the central questions in macroeconomics is "What does monetary policy do?"[1] More recently, there has been an increased focus on the *heterogeneous* effects of monetary policy on different socio-economic groups, and in particular how monetary policy affects labor market outcomes across these different groups. In this paper, we focus on subgroups of the population that are often the focus of public discourse: We study the effects of monetary policy on subgroups of the population defined by education, gender, marital status, and race.[2]

A common approach to answering this question for *aggregate* variables is to model the dynamics of a vector of variables via a vector autoregression (VAR) and then invoke an identifying assumption that maps forecast errors into an estimate of the monetary policy shock (see for example the work surveyed in Christiano et al. (1999)). We use the VAR approach to study the effects of monetary policy, but instead of focusing on aggregate variables alone, we use U.S. micro data to augment aggregate VARs with data on labor market outcomes of the socio-economic groups of interest. Our focus in this paper is on the unemployment rate, where we find dramatic differences across these groups. For example, the peak effect for men without a high school degree is double the peak effect for the aggregate unemployment rate. Furthermore, we often find that the peak effect of the differences in the unemployment rate across groups is at least 50 percent of the aggregate peak response. The response of the aggregate unemployment rate to a monetary shock, thus, masks substantial heterogeneity in the population.

Over the last decade, the economics profession has started to study the effects of monetary policy changes on individuals. Our study focuses on time series methods and complements work such as Bergman et al. (2022), which has an applied micro focus in terms of methods - the authors use variation across metropolitan areas to assess the heterogeneous effects of monetary policy on workers with different labor force attachments. Another approach uses heterogeneous-agent versions of equilibrium models that have long been used to analyze monetary policy (Kaplan et al., 2018; Gornemann et al., 2016; Auclert, 2019). While these

[1] This is also the title of Leeper et al. (1996), which inspired our own choice of title.

[2] Our choices for slicing the micro data result in overlapping groups - individuals appear in different groups in our different exercises.

equilibrium models feature rich heterogeneity, this heterogeneity is usually summarized by a few state variables at the household level (e.g. various asset positions or the current income level). These models, while tremendously useful, thus do not yet contain heterogeneity along many dimensions that (i) economists find useful to study and (ii) that are prominent in public discourse, for example, education, gender, race, and marital status, to name just the three dimensions we will focus on this paper.[3] Empirically, Holm et al. (2021) use Norwegian micro data to empirically assess the impact of monetary policy shocks on individuals along the wealth distribution, while Andersen et al. (2020) use Danish micro data to study the effects of monetary policy on households along the income distribution. Both of those papers thus focus on measures of heterogeneity commonly present in the aforementioned equilibrium models.

The issue of heterogeneous effects of monetary policy more broadly has been touched upon in various studies - besides the aforementioned studies, Bartscher et al. (2021) study the effects of monetary policy on the black/white unemployment gap, while Doepke and Schneider (2006) study the effects of inflation, partly controlled by monetary policy, on wealth inequality. Coibion et al. (2017) use VARs to study the effects on inequality just like we do, but they focus on broad summary measures of income and consumption inequality, whereas our focus is on differences in labor market outcomes across socio-economic groups. Similar to Coibion et al. (2017), Lenza and Slacalek (2018) analyze the effects of monetary policy (and quantitative easing in particular) on wealth and income inequality in the Euro Area.

To identify monetary policy shocks, we exploit variation in Federal Funds futures around Federal Open Market Committee (FOMC) meeting dates. We, hence, extend the monetary policy instrument from Gertler and Karadi (2015). Our approach to incorporating instruments in VARs is borrowed from Mertens and Ravn (2013).

The next section discusses our data. We then briefly introduce our VAR models before we show results from our procedure for aggregate and aggregated data as a benchmark. Section 5 contains our main results on the effects of monetary policy shocks across different socio-economic groups.

2 Data

Our VARs combine aggregate macro data with labor market data for various socio-economic groups that we aggregate from micro data. To aggregate the micro data, we use uniform extracts from the Current Population Survey (CPS) outgoing rotation group provided by the Center for Economic and Policy Research (`ceprdata.org`). We use micro data on hours, la-

[3]One notable exception is Nakajima (2021), who studies racial inequality in such a model.

bor force participation, wages, and unemployment status. We extend the sample in Gertler and Karadi (2015): the data starts in July 1979 and ends in December 2019.[4] We only study prime age individuals throughout. Unemployment rates and labor force participation rates are constructed as rates in the relevant groups: If, for example, everyone in one socio-economic group who is part of the labor force had a job, the unemployment rate in that group would be 1 irrespective of developments in other groups.[5]

The macro series are the same as in Gertler and Karadi (2015): the one-year government bond rate, the excess bond premium (Gilchrist and Zakrajsek, 2012), the log of the Consumer Price Index (CPI) as well as the log of industrial production. All data series are seasonally adjusted.

3 Our VAR Model

We model all vectors of variables we are studying as follows:

$$\mathbf{y}_t = \mathbf{m} + \sum_{\ell=1}^{\mathcal{L}} \mathbf{A}_\ell \mathbf{y}_{t-\ell} + \mathbf{u}_t \tag{1}$$

where we set the lag length $\mathcal{L}$ to 12 since we use monthly data. To identify a monetary policy shock, we are looking to identify one column of a matrix $\mathbf{\Sigma}$ such that

$$\mathbf{u}_t = \mathbf{\Sigma}\mathbf{e}_t \tag{2}$$

We borrow our approach to identification from Mertens and Ravn (2013), who show how to use an instrument for a structural shock to identify said shock in a VAR. [6] In particular, we use an observed measure of a monetary policy shock $\mathbf{m}_t$ that has to satisfy the following two

[4]Details on data sources and the construction of the instrument can be found in Appendix A.

[5]We use a 3 point moving average filter to remove measurement error from the micro data. These filters are common in signal processing, where they are called finite impulse response filters. Our benchmark is a one-sided centered version of this filter, but we show in the appendix that our results are robust to using a two-sided version as well.

[6]As highlighted by Jentsch and Lunsford (2019), the original bootstrap procedure used by Mertens and Ravn (2013) can be problematic. For inference, we employ the delta method proposed by Montiel Olea et al. (2020) and subsequently used by Mertens and Ravn (2019). We show in the appendix that our results are robust to using the parametric bootstrap of Montiel Olea et al. (2020) instead.

restrictions:

$$E(\mathbf{m}_t \mathbf{e^m}_t) = \Phi \qquad \text{[relevance condition]} \tag{3}$$

$$E(\mathbf{m}_t \mathbf{e^r}_t) = \mathbf{0} \qquad \text{[exogeneity condition]} \tag{4}$$

where Φ is an unknown non-zero scalar, $\mathbf{e^m}_t$ is the monetary policy shock we want to identify, $\mathbf{e^r}_t$ are all other structural shocks such that $[\mathbf{e^m}_t \; \mathbf{e^{r\prime}}_t]' = \mathbf{e}_t$, and $\mathbf{0}$ is a conformable matrix of zeros. Our choice of instrument is the surprise in Federal Open Market Committee (FOMC) dates in the three month ahead monthly Fed Funds futures, which is also the benchmark choice in Gertler and Karadi (2015).

One issue to keep in mind with this approach is that the impulse responses (IRFs) are only identified up to scale, as highlighted by Stock and Watson (2018). We scale all impulse responses so that the initial impact of a monetary policy shock is a 25 basis point increase in the short-term nominal interest rate. We run separate VARs for each socio-economic group. While these VARs allow us to get a sense of different responses across different socio-economic groups, they cannot help us to get a sense whether the differences are statistically significant or not since we need the joint distribution of the impulse responses across socio-economic groups for such statements. We, therefore, also run VARs where we keep the aggregate variables as before, but now introduce the differences in labor market outcomes between any two socio-economic groups instead of the levels of the outcomes for one group alone. These additional VARs and their associated responses to a monetary policy shock allow us to assess statistical significance of the differences in impulse responses by studying the impulse responses of the differences in outcomes.

4 Aggregate Results

To assess whether our micro data is sensible, we do the following: (i) we aggregate our micro data and compare it to their aggregate counterpart, and (ii) we run a VAR with those aggregated data as well as our standard aggregate data to check if the impulse responses to a monetary shock look reasonable. This is especially important given the contributions by Ramey (2016) and Bu et al. (2020), who find that identification of monetary shocks could lead to counter-intuitive results if the sample is not informative enough about the effects of monetary shocks.

Figure 1 shows the aggregated data versus corresponding aggregate data[7] as well as selected results from the VAR with aggregated variables. Our aggregated unemployment rate calcu-

[7] Since the responses of unemployment rates are the main focus of this paper, we focus on them here.

lated from CPS data tracks the aggregate unemployment rate closely. Concerning impulse responses for aggregate and aggregated variables, our results are standard: the short-term interest rate (labelled GS1 in Figure 1) increases on impact (this is due to our normalization), but stays positive for one year. The price level decreases (in particular, we do not find a price puzzle of the type that has often plagued this literature (Sims, 1992)), and industrial production (IP) decreases. As for the aggregated variables, the unemployment rate (UR) increases,[8] and labor force participation (LFP) shows a persistent decrease after a short increase.

For the VARs with disaggregated data shown below, we display only responses of the relevant disaggregated data. The responses of the aggregate variables in those VARs are broadly in line with the results shown in Figure 1.

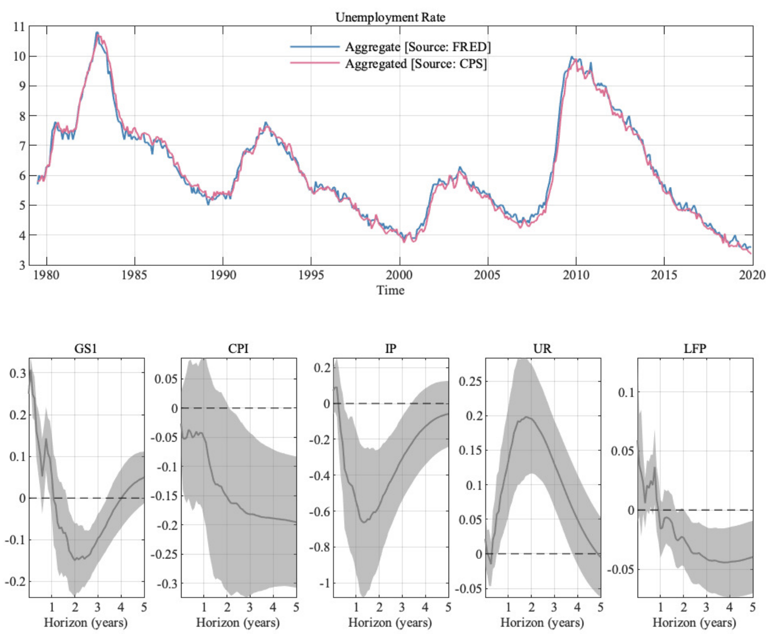

Figure 1: Impulse responses of the VAR with aggregate variables and aggregated versions of our micro data. Error bands are 68% significance bands computed using the delta method.

5 Disaggregated Results

We now turn to describing how the labor market outcomes of various socio-economic groups change after a monetary policy shock. The figures show the time series of the relevant labor

[8]The response of the unemployment rate is similar to other results reported in the literature, see, for example, Figure 2 in Ramey (2016).

market variable for the different subgroups in the top panel and the impulse responses for each subgroup in the middle row (with the response for the aggregated variable from the previous section also displayed in gray). The bottom row shows the impulse response of the difference between two of the groups. [9]

5.1 Education

Education has long been identified as a major determinant of economic outcomes. We, therefore, begin our study of the potentially heterogeneous effects of monetary policy on labor market outcomes by studying education. We intentionally use a relatively coarse set of groups so that we can later interact it with other characteristics while keeping the (cross-sectional) sample sizes meaningful - less than high school (i.e. less than 12 years of schooling), less than a college degree (but a high school degree), and finally an undergraduate college degree or more (titled "AboveCollege"). As is well known, the unemployment rate of people with at least a college degree is not only substantially lower than for the other groups, but also less volatile, as can be seen from the top panel of figure 2. The effects on the levels of the unemployment rate differ substantially across these groups, as the unemployment rate of those with at least a college degree reacts substantially less than for the other groups or our aggregated unemployment rate, which we show in gray in each panel in the middle row. The response of the aggregated unemployment rate can be above or below thew group-specific responses. We discuss this result in detail in Section 6. The bottom panel shows that differences between the most educated group and the others are long-lived, with the effects of monetary policy shocks being more severe the less educated a group is. The differences between the two less educated groups, on the other hand, are neither statistically nor economically significant. The magnitude of the response of the differences can amount to about 0.3 percentage points of the unemployment rate, which is roughly the magnitude of the peak response of the aggregate unemployment rate (in gray in the middle row). These differences are economically meaningful and, as we will see below, they can become larger as we dig deeper into the heterogeneity among different socio-economic groups.

The fact that less skilled workers are more likely to experience unemployment during recessions (Heathcote et al., 2020) is thus also true for downturns driven by monetary policy.[10]

[9] The impulse responses in the bottom row are not just the differences of the impulse responses in the middle row, as the VARs used to obtain the impulse responses in the bottom row use a different information set (lags of the differences across the groups feature as endogenous variables in those VARs).

[10] Further evidence for this hypothesis is provided in Jefferson (2005), who uses distributed lag models to compute cumulative multipliers of monetary policy shocks on relative unemployment rates. He does not use CPS data and is hence more limited in the sample length, which is just shy of 12 years in his case, whereas we use over 30 years of data in our VAR.

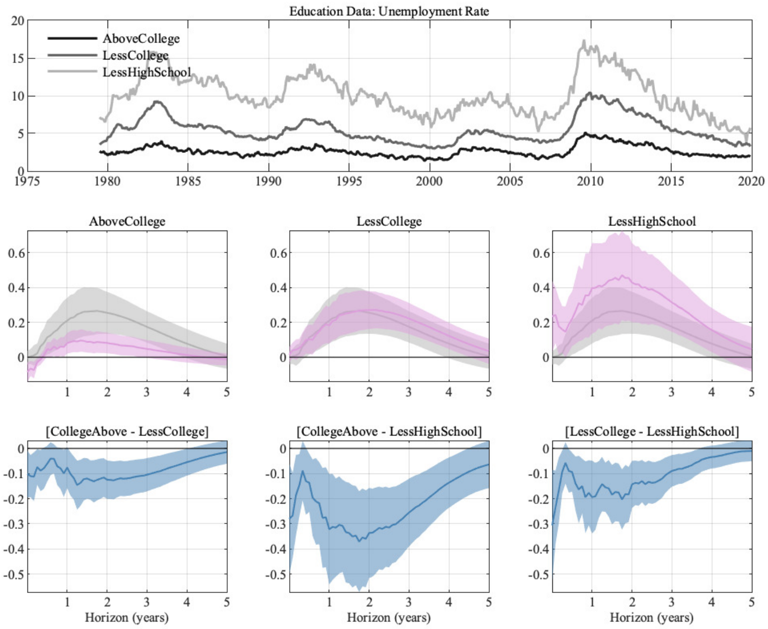

Figure 2: Results for different education levels. Error bands are 68% significance bands computed using the delta method.

5.2 Education and Gender

We now dig deeper into the micro data to assess whether the splitting of survey participants into education groups alone was hiding further heterogeneity. To do so, we use the same education grouping as before, but further split by gender.[11] The results are shown in Figure 3.

While the male unemployment rate clearly increases less the higher the level of education, for women the picture is not as clear: while the point estimate is smaller for more educated women, the uncertainty surrounding the responses for less educated women is much larger. Studying the IRFs of the differences in unemployment rates across these groups, we find that when comparing the same education level across gender (the first three plots in the third row), the unemployment rate increases significantly more for males. This increase is larger the less educated a group is. In terms of education, the differences for a given gender (as displayed in the last two plots of the third row) between the most educated and the least educated groups are not only statistically significant, the maximum responses of the differences for males are *larger* than the maximum response of the *level of the aggregate*

[11] Differences in economic outcomes across genders have long been a key issue studied by economists. For recent work, see, for example, Guvenen et al. (2020).

unemployment rate. For females, this response is smaller, but still close to the magnitude of the aggregate unemployment rate response.

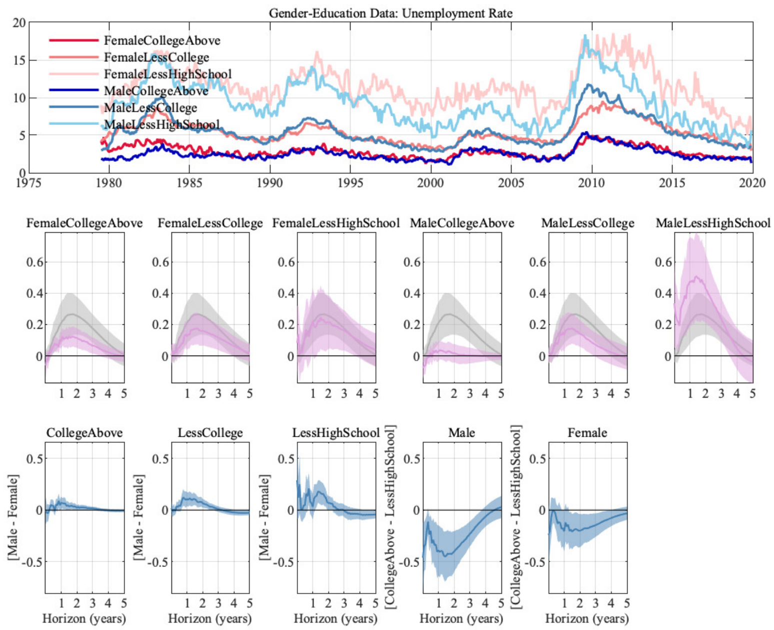

Figure 3: Results for different education and gender levels. Error bands are 68% significance bands computed using the delta method.

5.3 Gender and Marital Status

To understand the differential responses of males and females deeper, we now split our micro data across both gender and marital status.[12]

For both females and males, we see a larger response of singles. Singles are hit harder by a contractionary monetary policy shock, but also benefit more from an expansionary monetary shock. Single males are the only group in this stratification whose unemployment rate has a larger peak response than the aggregate unemployment rate. The differences across groups can again be as large as the peak response of the aggregate unemployment rate, as can be seen from the bottom row of Figure 4.

[12]To keep the samples sizes for the micro data reasonable, we drop the education level in this section.

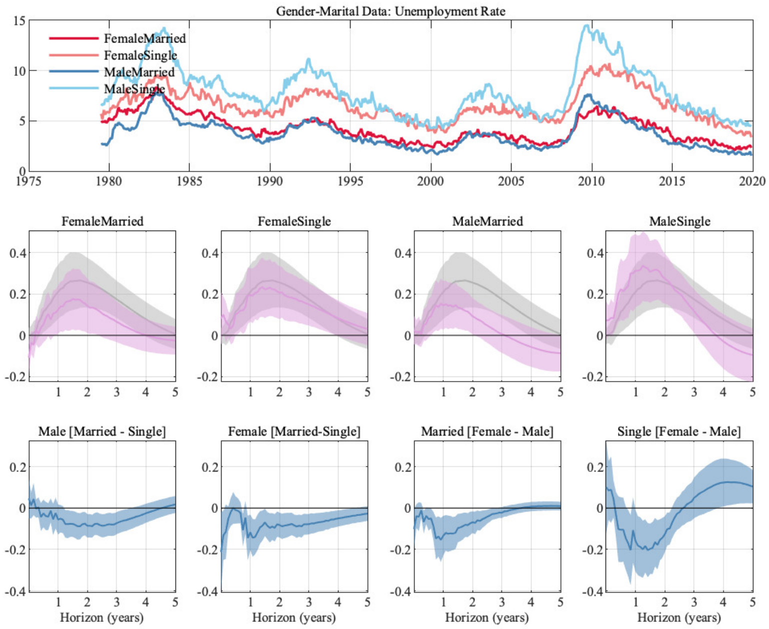

Figure 4: Results across marital status and gender. Error bands are 68% significance bands computed using the delta method.

5.4 Additional Results

In this section, we discuss two additional sets of results: (i) the importance of race, and (ii) the heterogeneous effects of monetary policy shocks on labor force participation.

5.4.1 Race and Gender

Racial inequality and its interplay with monetary policy has been the focus of a number of recent papers (Bartscher et al., 2021; Nakajima, 2021; Lee et al., 2022). While we, therefore, chose to focus on other dimensions of heterogeneity in this paper, we want to highlight that race is an important dimension along which there is substantial heterogeneity. Figure 5 shows the impulse responses for African-American males and females as well as the corresponding Caucasian groups. The one group that has larger peak effects than the aggregate unemployment rate is African-American males. The differences, both with respect to the aggregate unemployment response, as well as to the other disaggregated groups, are startling. Interestingly, the unemployment responses of Caucasian and African-American females are very similar. These differences and similarities across groups mirror findings from Chetty et al. (2019), who study the black-white income gap and find that it is driven by differences between African-American and Caucasian males. We find that these groups also react very differently to monetary policy shocks. Because we use linear models, positive and negative shocks have symmetric effects. Expansionary monetary policy shocks, thus, close the gap in unemployment rates between African-American males and other groups according to our results.[13].

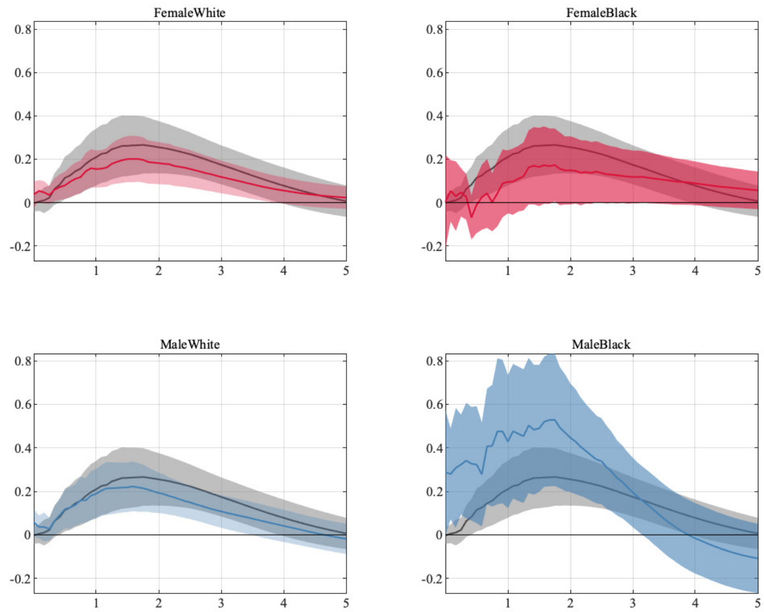

Figure 5: Results for gender-race UR.

5.4.2 Labor Force Participation

While the main focus of our study is on the unemployment rate, we find it useful to also consider how labor force participation (LFP) varies across the groups that we study, highlighting how our results are related to other work in macroeconomics.

We show in Figure A-10 in the Appendix the responses of the level of LFP for different groups (as well as for our aggregated version of LFP).[14]

As with the unemployment rate, various different groups have much larger swings in labor force participation than those we see for the aggregated variable (in gray in the last panel of the second row). However, another pattern emerges: Some groups change their labor

[13] African-American unemployment rates are generally higher than for whites (see, for example, Lee et al. (2022).

[14] We moved Figure A-10 to the Appendix due to the space constraints of the journal.

force participation in the *opposite* direction relative to the aggregate response. In particular, women with at least a college degree and those that are married increase their labor force participation rate in response to a contractionary monetary policy shock. The same is true for men with at least a college degree, even though their response is much more muted compared to the one observed for females with the same level of education.

There is by now a growing literature highlighting how women's labor market participation has changed and how a woman's labor market status may change to smooth shocks faced by the entire family (Albanesi, 2019; Doepke and Tertilt, 2016; Gorbachev, 2016; Ellieroth, 2019). Our results show that over our sample married women entered the labor force, possibly to counteract the prospect of job loss by their spouse. The aggregate negative response of LFP seems to be mainly driven by male and female singles.

6 Disaggregation - Some Analytics

Throughout this paper we have found that group-specific impulse responses can be either smaller or larger than the impulse response of the aggregate unemployment rate. To understand possible sources of this result, consider the following stylized environment: We have at our disposal data on a unit-variance economic shock ε_t (for simplicity, we abstract here from mismeasurement that we allow for in our empirical work) as well as two (mean zero) data series $x_{1,t}$ and $x_{2,t}$, which we can aggregate into $x_t \equiv ax_{1,t} + bx_{2,t}$, where a and b are non-negative weights used for aggregating micro data into one data series. To further simplify this example, we (i) assume all data are independently and identically distributed (iid), and (ii) focus on population regressions, i.e. the hypothetical scenario where we have access to an infinite amount of data. In such a situation, we could recover the impact effect of the monetary shock on disaggregated and aggregated variables, i.e. the population regression coefficients α, α_1, and α_2 in the following three regressions:

$$x_t = \alpha\ \varepsilon_t + u_t \tag{5}$$

$$x_{1,t} = \alpha_1\ \varepsilon_t + u_t^1 \tag{6}$$

$$x_{2,t} = \alpha_2\ \varepsilon_t + u_t^2 \tag{7}$$

u_t, u_t^1, u_t^2 are the regression residuals. The question we want to investigate is how the weights a and b in the data construction are linked to a weight w defined via:

$$\alpha = w\alpha_1 + (1 - w)\alpha_2 \tag{8}$$

This weight summarizes how heavily the impact response of $x_{1,t}$ influences the impact response of aggregated data x_t. Using the standard OLS formula and the fact that the variance of ε_t is 1, we find that

$$w = \frac{a * cov(x_{1,t}, \varepsilon_t) + (b-1) * cov(x_{2,t}, \varepsilon_t)}{cov(x_{1,t}, \varepsilon_t) - cov(x_{2,t}, \varepsilon_t)} \tag{9}$$

The weight w depends on the weights a and b used in aggregation and the larger a, the larger the weight w. Furthermore, we can see from the data series in our earlier plots that groups that have large IRFs usually have more volatile unemployment series. If part of that volatility is driven by monetary shocks then the covariance of that group's outcome with the monetary shock is larger than for other groups, leading to an even larger weight w, as is evident from equation (9). It is, thus, not surprising that the responses of larger groups in the population that also have more volatile unemployment rates, such as single males, have a large influence on the IRF of the aggregated unemployment series.

7 Conclusion

We have used standard macroeconomic identification assumptions in conjunction with well-known micro data on labor market outcomes to shed light on how the unemployment rate (and labor force participation) for different groups react to monetary policy shocks.

We find substantial heterogeneity across individuals in the US when it comes to the sensitivity to monetary policy shocks. The impulse response of the differences across groups often has a peak that is as large in magnitude as the peak of the response of the aggregate unemployment rate. Aggregate responses, thus, mask a large amount of heterogeneity across groups: less educated individuals show a substantially larger sensitivity to monetary policy shocks, as do single males (with there certainly being substantial overlap between these two groups).

Dynamic equilibrium models (Auclert, 2019; Kaplan et al., 2018; Gornemann et al., 2016) highlight channels that can lead to substantial heterogeneity in individuals' responses to monetary policy shocks. An interesting question for future research is whether the frictions already present in these models are enough to account for our findings or if additional frictions related to the groups we studied are needed. While we normalized our impulse responses to show a contractionary monetary policy shock, this also means that these more sensitive groups benefit more from expansionary policy than what one would expect from looking at the aggregate impulse responses alone.

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Appendix For "What Does Monetary Policy Do To Different People?"

A Data

A.1 Aggregate Data Sources

We downloaded the following aggregate macroeconomic data from the FRED database with the respective mnemonics in parentheses: *Industrial Production: Total Index* (INDPRO), *Consumer Price Index for All Urban Consumers* (CPIAUCSL), *Unemployment rate*, (UNRATE), *1-year government bond rate* (GS1), *GZ excess bond premium*, *Average Hourly Earnings* (AHETPI), *Average Weekly Hours* (AWHMAN) and *Labor Force Participation Rate* (CIVPART).

A.2 Micro Data Sources

We downloaded CEPR Uniform Extracts of the CPS ORG version 2.5 from CEPR data. The sample ranges from 1979 to 2019. We drop all persons with age less than 25 or more than 54 to keep prime age workers only. All group specific labor variables are calculated based on the final weights (fnlwgt). The hours are based on reported "usual hours" (uhourse) and we only keep observations with positive hours.
There has been a major redesign of the CPS in 1994. This results in sudden breaks of hours for certain demographic groups. We follow the procedure described in Braun et al. (2018) to remove the breaks in those series. We first find the average change in each series from December to January for all year expect 1993-1994. We then multiply the first part of each series (January 1979 through December 1993) by a constant such that the change from December 1993 to January 1994 is equal to the average December-January jump of all other years. Afterwards, all series are seasonally adjusted using the default settings of Census X-13 method implemented in Eviews 11.

A.3 Instrument Construction

The construction of the our monetary policy shock instrument is based on Gertler and Karadi (2015) and Gürkaynak et al. (2022). In particular, we use the high frequency data of 3 months ahead Federal Funds Future contracts provided by Gürkaynak et al. (2022) to construct the policy instrument. We aggregate to monthly series by summing up all daily surprises of the particular month. The sample of the instrument ranges from 1991M1 to 2018M12.

B Noise Filtering

To remove noise from the raw micro data we employ a 3-point moving average filter. To highlight that our findings are robust, we show results with a one-sided filter in this appendix (the results for the two-sided filter are in the main text). Let us denote the noisy time t raw data by x_t. For the two-sided filter we implement

$$y_t \quad = a_1 x_{t+1} + a_2 x_t + a_3 x_{t-1} \tag{A-1}$$

with y_t denoting the corresponding time t noise filtered data and corresponding weights $a_1 = .25$, $a_2 = .5$ and $a_3 = .25$. For the one-sided filter we implement

$$y_t \quad = a_1 x_t + a_2 x_{t-1} + a_3 x_{t-2} \tag{A-2}$$

with corresponding weights $a_1 = .5$, $a_2 = .25$ and $a_3 = .25$. In Figure A-1 we show the comparison of raw, one-sided and two-sided filtered time series of our aggregated unemployment data.

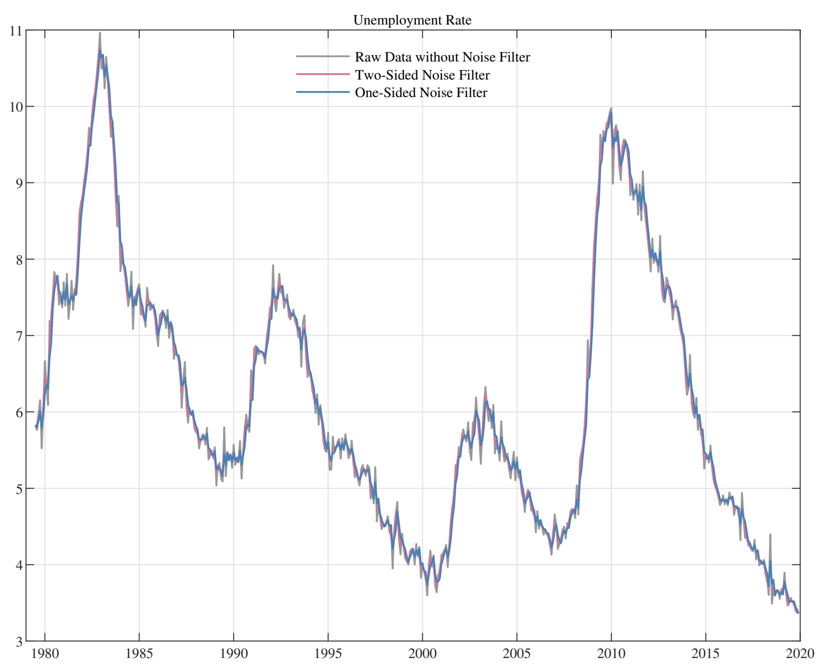

Figure A-1: Raw data versus one-sided and two-sided filter applied to our aggregated unemployment data.

C Additional Impulse Response Graphs

C.0.1 Results with Two-sided Filter

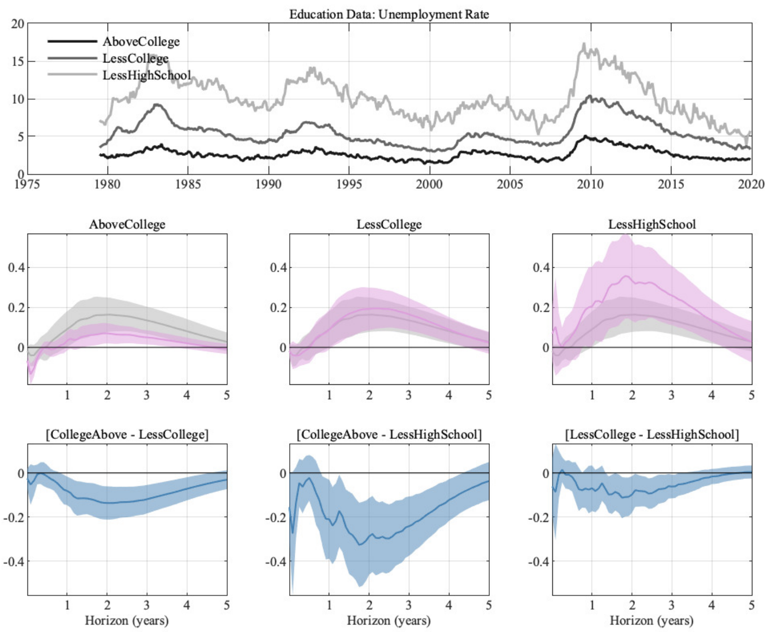

Figure A-2: Results for different education levels. Error bands are 68% significance bands computed using the delta method.

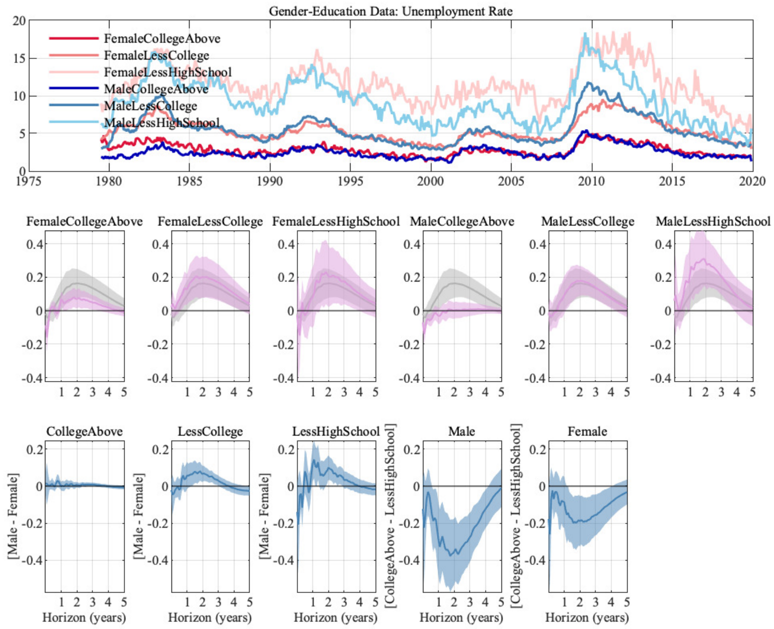

Figure A-3: Results for different education and gender levels. Error bands are 68% significance bands computed using the delta method.

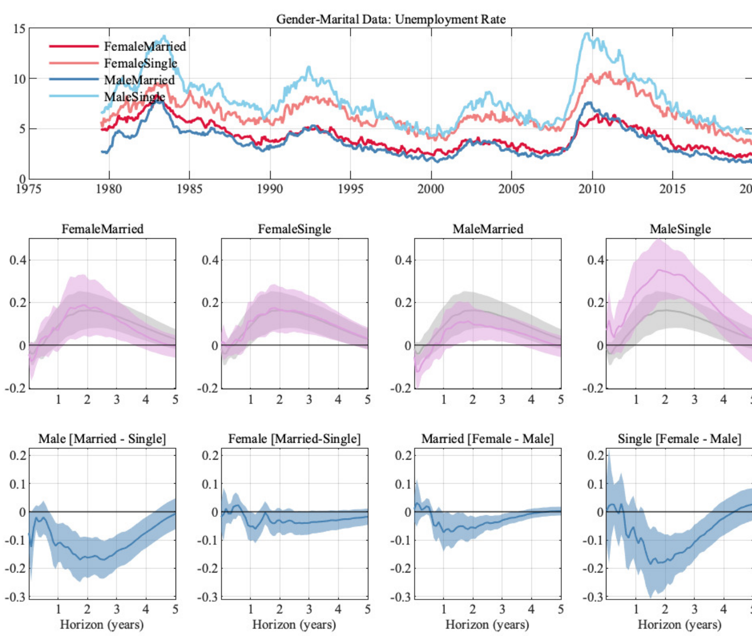

Figure A-4: Results across marital status and gender. Error bands are 68% significance bands computed using the delta method.

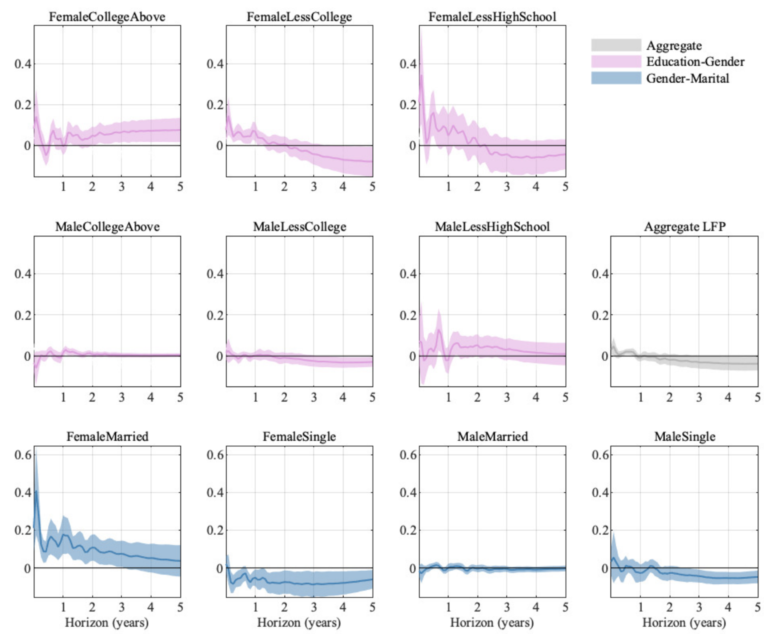

Figure A-5: Impulse responses of the labor force participation rate across groups. Error bands are 68% significance bands computed using the delta method.

C.1 Alternative Computation of Confidence Intervals

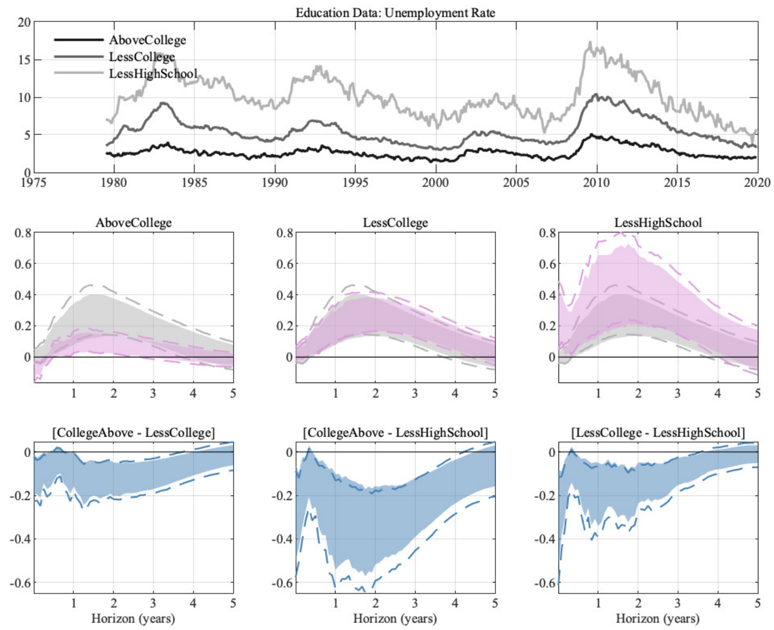

Figure A-6: Results for different education levels. Dashed error bands are 68% significance bands computed using the Montiel Olea et al. (2020) parametric bootstrap, shaded error bands use the delta method.

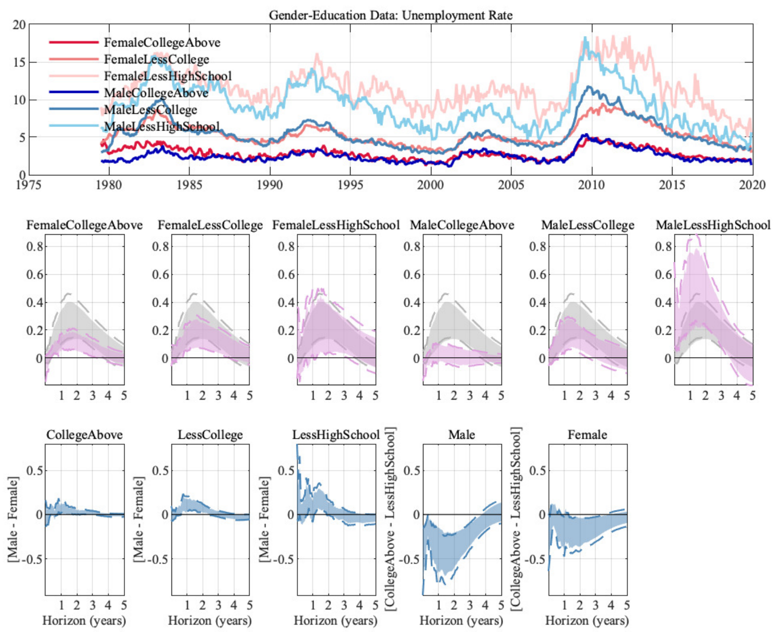

Figure A-7: Results for different education and gender levels. Dashed error bands are 68% significance bands computed using the Montiel Olea et al. (2020) parametric bootstrap, shaded error bands use the delta method.

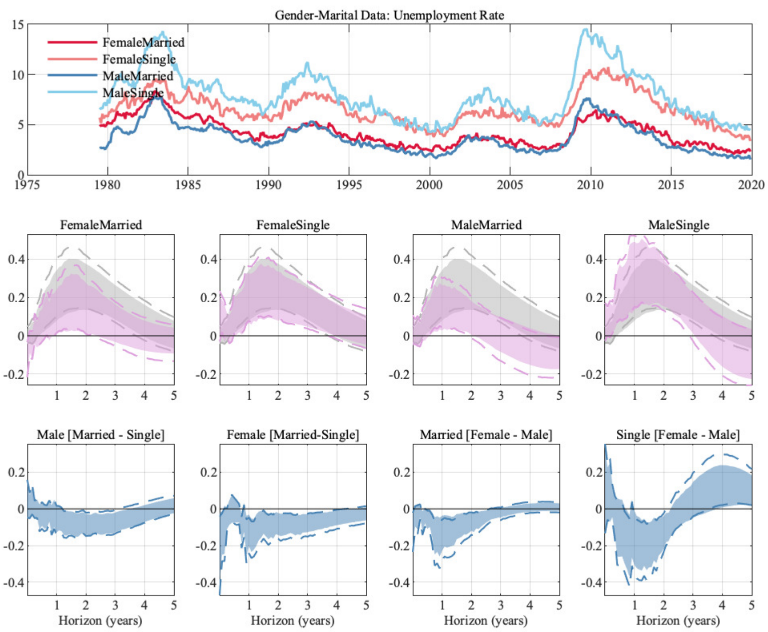

Figure A-8: Results across marital status and gender. Dashed error bands are 68% significance bands computed using the Montiel Olea et al. (2020) parametric bootstrap, shaded error bands use the delta method.

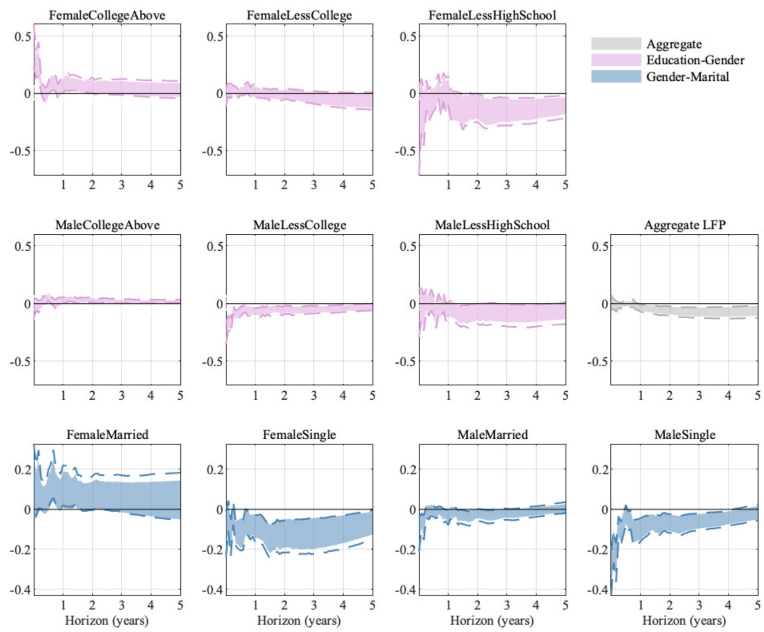

Figure A-9: Impulse responses of the labor force participation rate across groups. Dashed error bands are 68% significance bands computed using the Montiel Olea et al. (2020) parametric bootstrap, shaded error bands use the delta method.

D Labor Force Participation

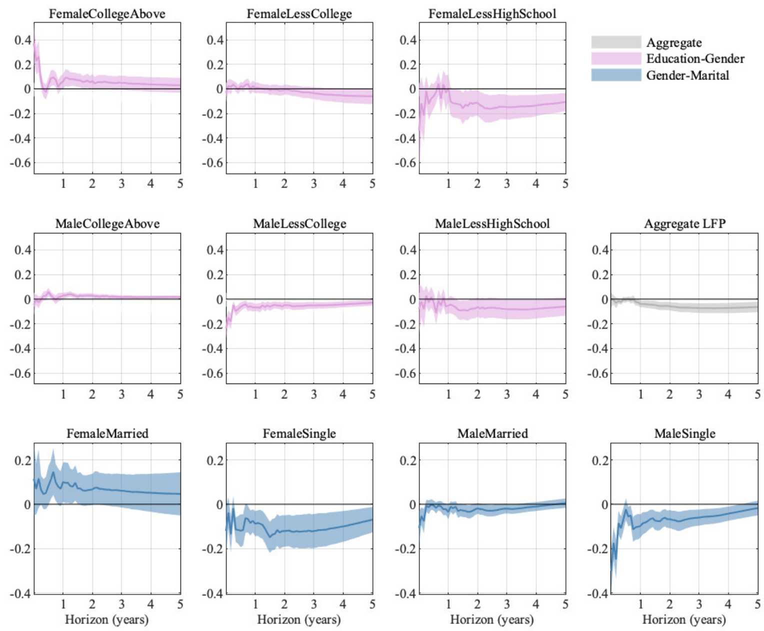

Figure A-10: Impulse responses of the labor force participation rate across groups. Error bands are 68% significance bands computed using the delta method.