Did COVID-19 induce a reallocation wave?*

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Abstract

Recent research has argued that the COVID-19 shock has also brought about a reallocation shock. We examine the evidence for such an occurrence in the United States, taking a broad perspective. We first consider micro data from CPS and JOLTS; there is no noticeable uptick in occupation or sector switches, nor churn, either at the aggregate level or the cross-section, or when broken down by firms' size. We then examine whether mismatch unemployment has risen as a result of the pandemic; using an off-the-shelf multisector search and matching model, there is little evidence for an important role for mismatch in driving the elevated unemployment rate. Finally, we employ a novel Bayesian SVAR framework with sign restrictions to identify a reallocation shock; we find that it has played a relatively minor role in explaining labor market patterns in the pandemic, at least relative to its importance in earlier episodes.

Keywords: Reallocation, COVID-19, mismatch. **JEL Codes**: E24, J63.

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Non-Technical Summary

An important policy debate that has emerged in the wake of the COVID-19 pandemic is whether it also induced structural changes in the labor market. The scale and nature of the shock has raised concerns that the effects on the labor market in the United States were of a more permanent nature, calling for a large job reallocation wave.

Whether a reallocation shock is already under way has important implications for the design of policy. Reallocation is a long process, as it involves search and matching costs and the need for upskilling, generating mismatch unemployment. If certain types of jobs are permanently destroyed, then generous unemployment insurance may disincentivize laid off workers from seeking other employment and building new skills, delaying the needed reallocation. Employee retention policies may also be inefficient in this context, as they provide temporary protection for jobs that will ultimately be lost. Finally, mismatch unemployment implies a higher NAIRU, a smaller output gap and hence calls for less accommodating monetary policy, in the lens of standard New Keynesian models.

In this paper, we critically examine the case for a pandemic-induced reallocation wave. We focus on the United States and take a broad perspective. First, we gauge whether reallocation patterns can already be seen in publicly available data, namely CPS and JOLTS. In the CPS, we show that there is no discernible uptick in the share of workers switching occupations or sectors and, in general, job-to-job transitions have remained stable. From JOLTS, we find that hires have recovered and helped to reduce unemployment following the initial spike in job separation. Taken together with the results of Barrero et al. (2020), these findings imply that reallocation may have yet to take off, but if it has, it is taking place within occupations and industries; however, employer transitions rates for employed workers also fail to show much change. Across firms, we do not find that the hiring behavior of large firms has changed by poaching more workers from small ones. Still, this could be consistent with substantial reallocation within these firms (via labor-saving technologies or polarizing hiring patterns), although it does not show up in the indicators of job switchers.

We then take an off-the-shelf multisector search and matching model to examine whether mismatch unemployment rose as a result of the pandemic. A reallocation shock should have led to a large and persistent rise in mismatch unemployment (as a share of total), as workers move to new and growing sectors. We find little evidence to support this view; by all measures, mismatch unemployment has been less than 1 percentage point during the whole of the pandemic. Just like Sahin et al. (2014) show for the aftermath of the Great Recession, mismatch unemployment has not been an important factor for the pandemic recovery either.

Finally, we look for evidence of a reallocation shock using a novel identification strategy in a Bayesian structural VAR model. We introduce a job reallocation shock, distinct from neutral technology, matching efficiency, labor supply, or wage bargaining shocks. There is little evidence to suggest that the job reallocation shock played an especially large role, relative to other episodes, in driving the labor market through the first year of the pandemic. Aggregate demand was the primary driver of unemployment, hires and layoffs, with all other shocks having similar contributions. This is consistent with the view of the COVID-19 shock as reflecting cycles in demand, lockdowns restrictions and supply bottlenecks.

1 Introduction

COVID-19 rendered an unprecedented shock to the global economy. In the United States, 25 million jobs were lost from February to April 2020, especially in contact intensive sectors, and even more switched to working from home. While the initial shock quickly receded, over a quarter of job losses from the initial shock had not been recovered a year later. As such, the scale and nature of the shock makes it possible that such effects will be persistent, through, e.g. a steeper adoption of digitalization, or even a switch of innovation towards teleworking technologies (Bloom et al. 2020).

The unequal sectoral effects of COVID-19 (Guerrieri et al. 2020) raise the question whether a reallocation shock is already under way. The size of a reallocation shock (see Barrero et al. 2020) has important implications for the design of policy. Reallocation involves search and matching costs and the need for upskilling, generating mismatch unemployment. If certain types of jobs are permanently destroyed, then generous unemployment insurance (UI) may disincentivize laid off workers from seeking other employment and building new skills, hence delaying the needed reallocation. Employee retention policies (such as short-time work or temporary unemployment schemes) may also be inefficient in this context, as they provide temporary protection for jobs that will ultimately be lost.

In this paper, we examine whether such a phenomenon can already be detected by publicly available data. As there is no unique way of tackling the issue, or even defining a reallocation shock, we take a holistic approach and rely on a variety of data sources and methods. The main contribution of this paper is to show that there is little evidence in publicly available to suggest that COVID-19 has induced a major reallocation shock. While reallocation of resources to their most productive use is an integral part of a market economy, and a crucial channel for productivity growth (Decker et al. 2017, Andrews et al. 2019), we do not find that a reallocation shock has been an especially important driver of the economy in the pandemic era, relative to earlier periods.

First, we note that after the first few months of the pandemic, the forward-looking expected reallocation rates measures of Barrero et al. (2020) have been revised substantially downwards to numbers only slightly above historical averages.[1] We then look for evidence of reallocation in Current Population Survey (CPS) data. We find no meaningful change in the share of workers switching occupations or sectors within the month,

[1]See https://www.frbatlanta.org/research/surveys/business-uncertainty?panel=1.

suggesting that any major reallocation would be taking place within occupations or sectors, which may not be consistent with the reallocation shock narrative. Job-to-job transitions (an indicator of within-sector reallocation) also remain close to historical average, however, despite an increase in quits towards Summer 2021. The situation is much the same when we consider sectoral data; the fraction of workers who stay in their sector is quite close to pre-pandemic rates across sectors.

Furthermore, while we confirm large relative creation and destruction magnitudes in aggregate data for April 2020, by comparing the hire and separation rates in the Job Openings and Labor Turnover Survey (JOLTS), we note that hires were back to pre-COVID levels relatively soon after the initial shock, despite much higher unemployment, and lower separations. Hires picked up more broadly in 2021, along with a large rebound in economic activity; the increase in quits also occurred alongside a reduction in layoffs, as firms replenished their labor stock, and vacancies were at all-time highs. Finally, newly-released size class data by JOLTS show that little of the new hires or separations during the initial shock occurred at the very largest firms (over 5000 employees), in line with pre-COVID data, but unlike expectations of large shifts of workers in large firms who are taking advantage of the pandemic to increase their size. In a nutshell, there is little evidence in CPS or JOLTS to suggest a reallocation shock is already occurring; to the extent worker churn has increased, it is primarily occurring within sectors and occupations.

We then take an alternative approach, by examining mismatch; in the presence of frictions to reallocation, a large reallocation shock should have led to an increase in labor market mismatch, as it takes time to move workers from declining sectors and occupations to booming ones, and hence an increase in mismatch unemployment. This is reminiscent of similar discussions in the aftermath of the Great Recession. We take an off-the-shelf search and matching model with heterogeneous sectors from Sahin et al. (2014) and perform their analysis for the pandemic sample. We find that, while mismatch unemployment has increased since the beginning of the pandemic, it still accounts for a small fraction of the total increase. As such, similar to the Great Recession, we find that the pandemic recession has not led to a substantial increase in mismatch unemployment, and the high unemployment levels can only partially be attributed to mismatch.

It should be noted that, in principle, our finding of a small role for reallocation shocks in driving the labor market may stem precisely from the presence of generous

UI, which disincentivizes workers from switching to growing sectors. The evidence so far do not point to such a mechanism. Under different research designs and data, Dube (2021), Bartik et al. (2020), and Finamor & Scott (2021) all fail to find that unemployment insurance extensions reduced employment gains after lockdowns were loosened. On the other hand, the presence of partially experience rated UI may work in the opposite way; employers that tend to layoff a higher share of employees pay higher taxes, resulting in large and economic meaningful variation across states (Auray & Fuller 2020). Half of all states waived all employer UI charges as part of the CARES Act, which could in theory lead increased layoffs.[2] Bartik et al. (2020) examine this angle and similarly find no evidence that UI expansion raised layoffs. Marinescu et al. (2021) show that UI did lead to reduced search effort, but did not affect vacancy creation; as labor markets tightness was low, job creation was unaffected.

In a final exercise, we gauge the different drivers of labor marker fluctuations during the pandemic, through the lens of a Bayesian Structural Vector Autoregression (SVAR) framework. We employ a novel identification strategy, using sign restrictions disciplined from a New Keynesian search and matching model Abbritti & Consolo (2022); in particular, we distinguish between reallocation shocks and other supply shocks. The results point to a relatively minor role for a reallocation shock in driving hires and separations over the pandemic period. Aggregate demand played a much larger role, with other shocks having more nuanced effects. This is not to say that reallocation does not matter; rather, our point is that if COVID did indeed induce a major reallocation shock, we should expect for the effects of reallocation to stand out in this period relative to previous ones. We instead find the role of the reallocation shock to be broadly in line with historical experience.

Relationship to the literature Our work is related to the new and burgeoning literature examining the employment and output effects of COVID-19. While our focus is empirical, it is useful to briefly consider theoretical work, particularly as it pertains to optimal policy. This is because a strong reallocation shock would, as stressed in Barrero et al. (2020), necessitate allowing creative destruction to run its course, limiting the use of countercyclical policies. Most prominent papers find diminished potency of monetary and fiscal policy under pandemic conditions, but still advocate for strong policy support. Guerrieri et al. (2020) provide conditions under which supply shocks can lead

[2]For details, see `https://taxfoundation.org/unemployment-insurance-tax-hikes-covid19/`.

to negative demand shocks that are larger than the supply shocks themselves, focusing on complementarities in consumption; optimal policy requires extended UI for affected sectors, while accomodative monetary policy prevents firm exits. Baqaee & Farhi (2020) use a multisector framework to show that negative sectoral supply shocks are stagflationary, but negative sectoral demand shocks deflationary, accounting instead for complementarities in production networks; in their model, each of these account for roughly half the aggregate output decline from February to May 2020. They find a large role for UI in reducing the fall in output. Guerrieri et al. (2021) consider optimal policy specifically under the possibility of a reallocation shock, shifting demand across sectors. Even though the shock becomes endogenously equivalent to a cost-push shock and breaks divine coincidence, the presence of downward nominal wage rigidity (preventing a wage contraction in shrinking sectors) results in an optimally higher aggregate inflation rate.

On the empirical side, Brinca et al. (2021) draw sign restrictions from the framework of Baumeister & Hamilton (2015) to disentangle demand and supply shocks at the sectoral level during the initial shock, and find that two-thirds of the drop in hours growth was due to lower labor supply. Forsythe et al. (2020) augment CPS data with job postings from Burning Glass, and find that not only did labor market slack rise by less than conventional measures suggested, but also that mismatch somewhat fell. While we find mismatch temporarily rose, our focus is on mismatch at the sector level; Forsythe et al. (2020) instead consider mismatch at the occupation level, and they note that an apparent within-firm reduction in job postings for college-educated workers has reduced the variance of tightness across labor markets, hence signaling declining mismatch. This is fully consistent with our results; depending on the specification (i.e. the richness of sectoral heterogeneity), we find either a temporarily higher sectoral mismatch, or little to no change in sectoral mismatch. The fact that occupational mismatch seems to have declined makes the case for a reallocation shock even weaker.

This paper is also related to the extensive literature that considers labor reallocation, and how this changes in the business cycle. The classic argument of Caballero & Hammour (2005) presents the two opposing forces operating in recessions; the cleansing force, which destroys unproductive firms and efficiently reallocates labor, and the weak demand force, which prevents productive businesses from growing. Evidence remains mixed; Chodorow-Reich & Wieland (2020) for instance, show that exposure to reallocation shocks has no effects on local unemployment during expansions, but does increase it in recessions. Foster et al. (2016), on the other hand, find that recessions in general lead to cleansing (in the sense that reallocation is productivity-enhancing), but that was not the case for the Great Recession. More broadly, research in the wake of the Great Recession (Hershbein & Kahn 2018) showed that job polarization, the switch away from routine jobs towards non-routine cognitive and manual jobs, occurs predominantly in downturns, when routine jobs are disproportionately destroyed. Jaimovich & Siu (2020) show that polarization implies jobless recoveries, as routine jobs are permanently lower. Nevertheless, evidence from Sahin et al. (2014) and Herz & van Rens (2020) indicate that mismatch unemployment moves with the cycle, and is not the result of policy inhibiting structural reallocation from taking effect.

Our work is also linked to the literature looking at how hires vary cyclically across firms of different size. Moscarini & Postel-Vinay (2012) argue that large firms possess an advantage in poaching workers who rise on the job ladder; this advantage is stronger in tight labor markets. As such, employment growth of large firms is much more procyclical than it is for small firms i.e. in downturns, employment growth is stronger in small firms. They show that this effect was strong in the Great Recession. Haltiwanger et al. (2018) refine this finding by showing that i) the higher employment procyclicality of large firms is also due to higher nonemployment flows; and ii) that even though large firms contract faster when unemployment is high, it is smaller firms that contract more when unemployment is *rising*. Our results show this was also the case for the COVID episode; larger firms contracted substantially less in the initial shock, but then also grew less in the recovery. By Summer 2021, when the labor market had substantially tightened, it appears that larger firms started to grow faster, in line with the predictions of the literature.

Finally, this paper is related to the literature looking at the impact of technology shocks on the labor market (see Galì 1999, Christiano et al. 2003). We augment a standard Bayesian structural VAR model with a job reallocation shock with a view to capturing the potentially large reallocation wave stemming from the pandemic crisis related to the asymmetric sectoral effect and sector-specific shares of home working. In doing so, we complement previous work on the role of technology shocks (Justiniano et al. 2011, Fisher 2006, Canova et al. 2010) by enriching the model with labor market flows (see also Shimer 2012), to focus on how job turnover help to disentangle neutral and reallocative effects during COVID. Canova et al. (2013) highlight the importance of job flows as, after a technology shock, the unemployment rate increases because of a large wave of layoffs and because the job-finding rate taking times to adjust. The initial impact of the COVID crisis, instead, had very little persistent effects on job separation and finding rates.

Structure of the paper In section 2 we briefly present the data used in the various exercises of the paper, which come from well-known publicly available sources. Then in section 3 we discuss the evidence for reallocation from cross-sectional microdata. In section 4 we present the mismatch analysis based on the multisector search and matching model, while in 5 we lay out and analyze results from our Bayesian SVAR framework. Section 6 concludes.

2 Data

Our primary data sources are the CPS and JOLTS. The CPS sample is composed of individuals aged 15 or over. We use the panelized version of CPS, using the approach of Nekarda (2009).[3] Job-to-job transitions are calculated as the share of workers who remain employed in consecutive months but report they are not working for the same employer, following the pioneering approach of Fallick & Fleischman (2004). A drawback of this approach is that a large number of respondents who are employed in consecutive months are reported as ”not in universe” for this question, but it is impossible to know why. Since 2007, and due to changes in interviewing practices, the share of non-respondents has been rising, potentially biasing the estimate. Fujita et al. (2021) develop a method to address this issue, and show that the deviation levels off by 2010, and the trends between the raw and corrected series co-move very well for the period we study. Nevertheless, we use all three measures provided by them.

We work with two-level NAICS sectors, and group some similar sectors together, as some have too few observations in each month to record transitions out of employment. We end up with 34 different sectors (down from 51 used in the detailed group two-digit classification in CPS).[4] We complement this analysis using data for the Job Openings and Labor Turnover Survey (JOLTS), a monthly survey of 16,000 establishments designed to capture worker flows in the US labor market, split by sector, and, as of 2020, also by firm size. We consider both types of splits (by 17 major sectors, and 6 size classes).

[3] We panelize using the code of Kevin Rinz, available at `kevinrinz.github.io/data.html`.
[4] See Petroulakis (2020) for details.

For the mismatch exercise, we follow Sahin et al. (2014) closely and assemble data from a variety of sources. We use sectoral vacancy data from JOLTS and unemployment counts from the CPS, at monthly frequencies, for 17 sectors. We also follow the methodology of Sahin et al. (2014) to estimate sectoral matching efficiency parameters and aggregate vacancy shares for a constant-returns to scale matching functions. We measure labor productivity for each sector by the ratio of sector value added from the Bureau of Economic Analysis to employment from the Bureau of Labor Statistics (BLS) Employment Survey. Finally, sectoral job destruction rates are given as the ratio of gross job losses to employment, with data from the former coming from the Business Employment Dynamics (BED) of the BLS. As Sahin et al. (2014) do, we impute monthly destruction rates from quarterly BED data.

Finally, the SVAR exercise includes six variables in monthly frequencies: the quarterly growth rate of industrial production, PCE inflation and nominal wage inflation (on an annual basis), as well as unemployment rate, hire and layoff rates (source is JOLTS). We take particular care in choosing the wage measure; the unique nature of the COVID-19 shock led to record-level unemployment but burdened disproportionately low-wage workers. As such, conventional measures such as hourly earnings *rose* considerably, but exclusively due to compositional effects, as also shown in Cajner et al. (2020). This would also mean that calculating wage growth based on this measure would have led to a positive spike in April 2020 and a negative one in April 2021 (through base effects). We instead use wage growth data from the Atlanta Fed Wage Growth Tracker, which calculates median hourly wage growth for continuing workers from CPS microdata.[5] This way, the measure implicitly addresses compositional concerns. Similarly, using quarterly growth in industrial production is also useful because annual rates incorporate substantial base effects. Some base effects likely plague PCE inflation, but we prefer to keep this on an annual basis to remain consistent with wage growth (where using a quarterly growth is not possible).

The choice of the sample period is determined by data availability of the job flows, which are only available starting in 2001, and the monthly data used in the VAR model run from January 2001 to August 2021. A longer sample would also include the large inflationary pressures from energy shocks, which would introduce unnecessary noise to our estimation.

[5]The Wage Growth Tracker reports a number of different measures; we use the weighted hourly series for the aggregate economy.

3 Is there a reallocation wave under way?

While the pandemic shock is transitory, a combination of search costs, defaults, uncertainty and structural change may imply the permanent loss of many jobs, as well as a long delay in creating new jobs. The results of Barrero et al. (2020) certainly point towards such a story. Using survey data, they show an increase in *expected* excess reallocation (sum of creation and destruction minus net employment change) of 2.4 times relative to pre-pandemic averages, at the firm level. They document that for every 10 jobs lost, 3 were created already within the first 2 months of the pandemic. Combining their results with historical data on recalls, they estimate that 42% of staffing reduction will lead to permanent job losses.

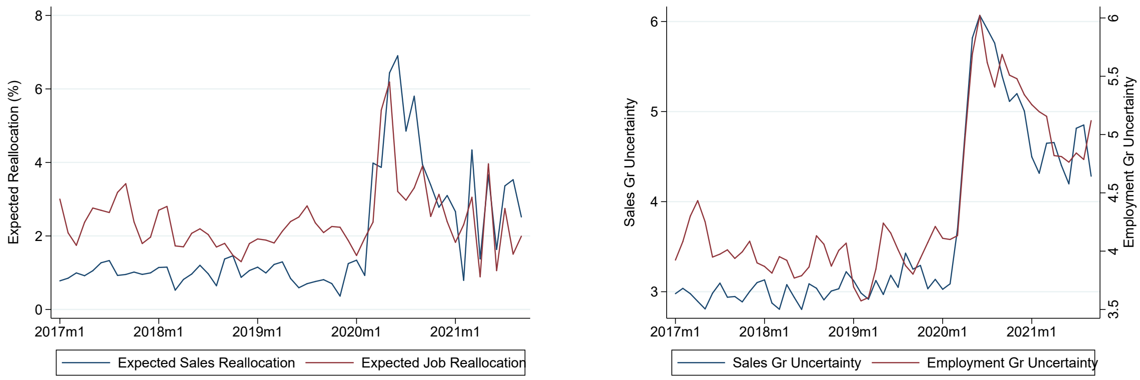
Since the publication of Barrero et al. (2020), expected job reallocation rates have been revised substantially downwards.[6] This is shown in the left-hand panel of figure 1. After rising almost three-fold relative to historical averages (and six-fold for sales reallocation) in the earlier stages of the pandemic, peaking in May 2020, job reallocation rates fell to numbers only slightly above historical averages. The data come from the Survey of Business Uncertainty, which surveys firms on their sales and staffing expectations. The measure of expected *excess* reallocation is constructed using expected employment changes over 12 months for growing and shrinking firms minus the absolute aggregate expected change. One possibility for the sharp revision in expectations of excess reallocation is the unprecedented nature of the shock, which also substantially raised uncertainty (measured as the weighted average standard deviation of growth forecasts across firms), and hence reduced the value of forecasts. Once uncertainty started falling (right-hand panel), so did expected reallocation, even though uncertainty remains high by historical standards. Another possibility is the return of furloughed employees, as temporary layoffs represented the bulk of employment losses early in the pandemic (Hall & Kudlyak 2020). On the other hand, it is possible that expected reallocation went down after the first pandemic wave as a large reallocation already took place and expected reallocation reverted to normal levels.[7]

[6] See https://www.frbatlanta.org/research/surveys/business-uncertainty?panel=1.

[7] In a follow-up paper, Barrero et al. (2021) use 12 month forward and backward reallocation data and show job reallocation at levels somewhat higher than historical values. Since this measure combines realized and expected reallocation, it is consistent with the view that a reallocation wave has already occurred. Moreover, a backward-looking measure will include the highly turbulent months of the early pandemic period, and it is unclear how informative it is about expected reallocation.

Figure 1: Business Expectations

(a) Reallocation (b) Uncertainty



Notes: The figures show 4-quarter ahead expectations of sales and job reallocation (left-hand side) and uncertainty (right-hand side) for a representative sample of firms, defined as in the text. Source:Atlanta Fed/Chicago Booth/Stanford Survey of Business Uncertainty. The series have been transformed to a 2-month moving average until February 2020. Sample is January 2017-August 2021.

3.1 Reallocation in the cross-section

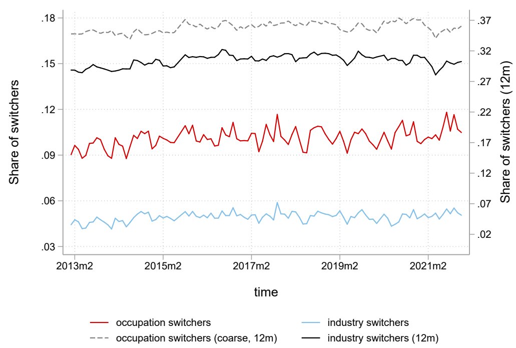
We then turn to the CPS to examine whether there is a noticeable shift of workers across occupations or sectors. This could include employed workers who switch employers or unemployed workers who take up a new job in a different occupation or sector relative to their previous employment. An increase in the fraction of workers who switch occupation or sector would point to increased reallocation. We calculate occupation and sector switchers as the fraction of workers who switch in adjacent months, both for continuing workers and for entrants from unemployment (as CPS codes the last known sector and occupation for unemployed workers). We also do this for switchers across 12 months, allowing us to also capture individuals present in the sample in later stages of the pandemic. For this measure we use the coarse 22 CPS major occupation classification, to correct for the erroneous switches problem notes by Fujita (2018), which are likely to be substantial across 12 months, especially since occupation codes changed in 2020.[8] We extend the sample to July 2021, when employment had risen substantially, and could give additional data points for reallocation. We exclude individuals recalled from a temporary layoff; while Fujita (2018), in a similar exercise, does include them,

[8]For the adjacent month comparison there is a resulting discrete jump in January 2020, which we remove (as well as June and July 2015, which exhibit a very large spike in the share of switchers). The 12-month measure can also be corrected similarly, but the coarse measure is more appropriate. Note also that focusing only on workers employed in consecutive months yields a qualitatively very similar picture.

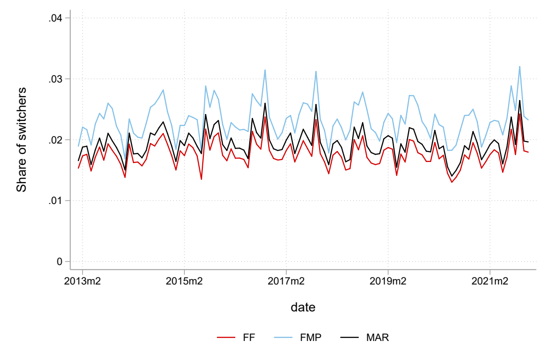
the spike in recalls would bias the switching rate downwards. We calculate job-to-job transitions as the share of workers who are employed in consecutive months but switch employers from one month to the other.

Figure 2: Share of workers switching occupations and sectors

(a) Occupation/Sector Switches



(b) Job-to-job transitions



Notes: The LHS chart shows the share of workers employed in consecutive months who switch occupations (4-digit, red line) or sectors (2-digit, blue line) from one month to another. The dashed gray line uses the CPS 22-occupation classification and shows occupation switches over 12 months, and the black line does the same for sectors. The RHS chart shows the share of workers who switch employers (job-to-job transitions); FF uses the Fallick & Fleischman (2004) measure, FMP the Fujita et al. (2021) measure, and MAR a measure assuming missing observations are missing at random. The sample for the LHS chart includes all CPS Basic Monthly Sample files from January 2012-November 2021. The data for the RHS chart come from Fujita et al. (2021).

We plot these measures in figure 2-a. The red and blue lines show the (non-seasonally adjusted) shares of workers employed in a given month who switch occupations (4-digit level) and sectors (2-digit level) relative to the previous month. There is no clearly discernible increase for either series. Following an upward trend coinciding with the recovery, the share of workers employed in consecutive months that switch occupations has hovered around 8% since 2016, and 5% for sectors.[9] The dashed gray line shows the occupation switching rates across 12 months, using the coarse measure; the black line shows the corresponding measure for industries. These are naturally higher, but the pattern is very similar, and also shows little movement during the COVID-19 shock. There is a visible short-lived fall in the share in April 2021, due to base effects (workers who did not lose their jobs in the initial shock were likely more attached), but the variation if overall small. This is especially interesting, since during later months of the shock, employment had substantially risen, and so a large reallocation wave would have been visible.

[9]Seasonally adjusted series display an even more muted pattern.

Figure 2-b plots the share of job-to-job transitions. We report three measures. FF denotes the standard measure by Fallick & Fleischman (2004), who pioneered using the CPS question on whether the interviewee is with the same employer to measure job-to-job transitions. FMP is a recent correction of FF by Fujita et al. (2021), in order to account for an increase in missing responses to this question in the CPS. Finally, MAR, also computed by Fujita et al. (2021), is a naive correction assuming that missing responses are missing at random. While the three measures do exhibit level differences in our sample, the overall pattern is very similar.

Job-to-job transition rates fell early in the pandemic, as expected, but then reverted close to historical patterns.[10] A small, but shortlived, pickup is noticeable towards the end of the sample (November 2021), which is consistent with the uptick in quits we document below; however, when considering seasonally adjusted rates (shown in figure 9 in the appendix) the pickup is much smaller. As the purpose here is only to see whether there is a spike in switching, not to analyze the cyclical properties of these series, we prefer to focus on non-seasonally adjusted rates. In any case, given that quits are at historical highs, we do eventually expect a pick-up in job-to-job transitions as well, but so far the picture does not suggest large reallocations occurring along that margin.

3.1.1 Sectoral patterns

Finally, we consider whether the muted switching pattern on aggregate is masking differences across sectors. A reallocation shock towards growing sectors could increase the share of stayers in these sectors, all the while reducing them in shrinking sectors, leaving the aggregate unaffected. To examine this, we show, in the top panel of figure 3, the share of workers who remain employed in the same sector they were employed in 12 months before the survey month, in a sample which also includes individuals who exit employment. The red bars show this average share for 2019, and also for part of the second half of 2021 (May-August). We consider the period starting 13 months after the initial shock to avoid having our estimates contaminated by base effects; since such a high share of workers were laid off in April 2020, the share of stayers in April 2021

[10] This measure can also include workers who are laid off and find a job prior to the CPS interview. The denominator consists only of individuals with a valid response to the relevant question, as a large number of eligible interviewees have missing values for this question, for unknown reasons. However, the stable value around 2% is consistent with estimates by Bosler & Petrosky-Nadeau (2016) with different data.

conditional on remaining employed in April 2020 is likely to be artificially high.[11]

As figure 3(a) shows, on aggregate, around 70% of workers remain employed in the same sector after 12 months, even accounting for exits to non-employment. This figure did not change between 2019 and 2021. Moreover, for almost all sectors, the change in the share of stayers is very small. In some sectors, such as Wholesale Trade and Information, it is even slightly higher. The only sector with a noticeable decline, from 69% to 64%, is Leisure, which includes both Accommodation and Food Services and Arts/Entertainment. This is to be expected, as this was by far the sector most affected by the pandemic, with many establishments going out of business, and workers having to seek work in other sectors.

Even in this case, however, evidence suggests that displaced workers transitioned to sectors with similar skill requirements; in California, over 60% of UI claimants from Accommodation and Food Services who transitioned found work in either Retail, Administration Support and Waste Management, Healthcare and Social Assistance, or Transportation and Warehousing.[12]

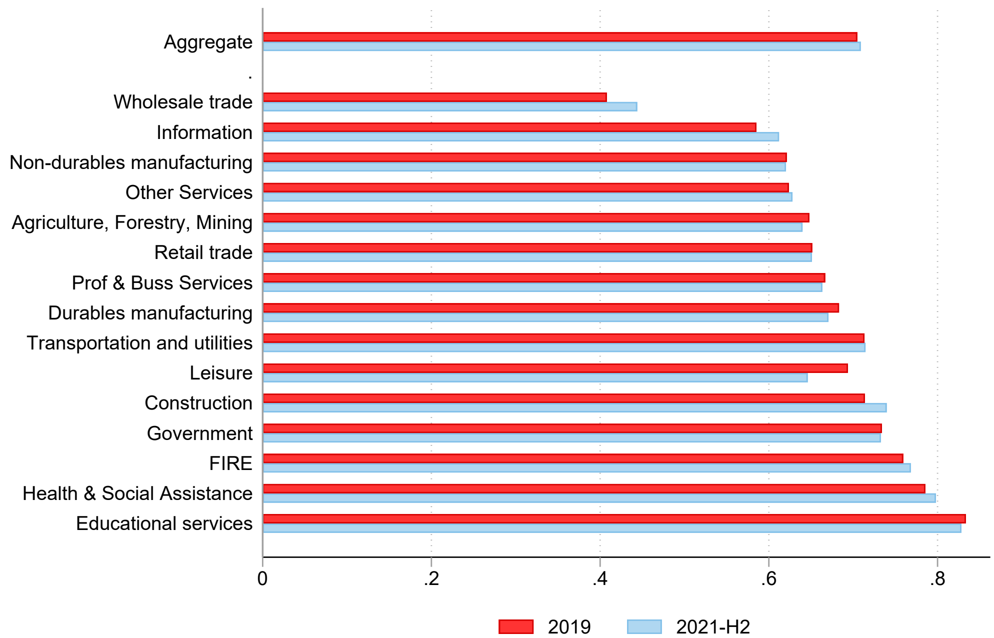
Focusing on the period after April 2021 corrects for base effects, but has the drawback of only looking at the period after the initial shock, hence missing the possibility for persistent reallocation occurring during the initial shock. As such, the bottom panel of figure 3 repeats the exercise for 2021-Q1 instead. In this case, we only include employed individuals in the sample, as joblesness was still high at that time, with employment to population ratio lower than the trough of the Great Recession. The situation is very similar in this case; on aggregate and across sectors, the share of workers employed in the same sector as a year earlier were very similar before and after the pandemic.

A shortcoming of the analysis above is the fact that it focuses exclusively on individuals employed 12 months before each given period. For April 2020 in particular, despite the fact that job losses were so high, given the rotating panel nature of the CPS, the sample contains too few workers present in both April 2020 and April 2021 and having lost their jobs in April 2020. However, data suggests that even those who lost their jobs in the initial shock had very high re-employment rates in the same sector. In par-

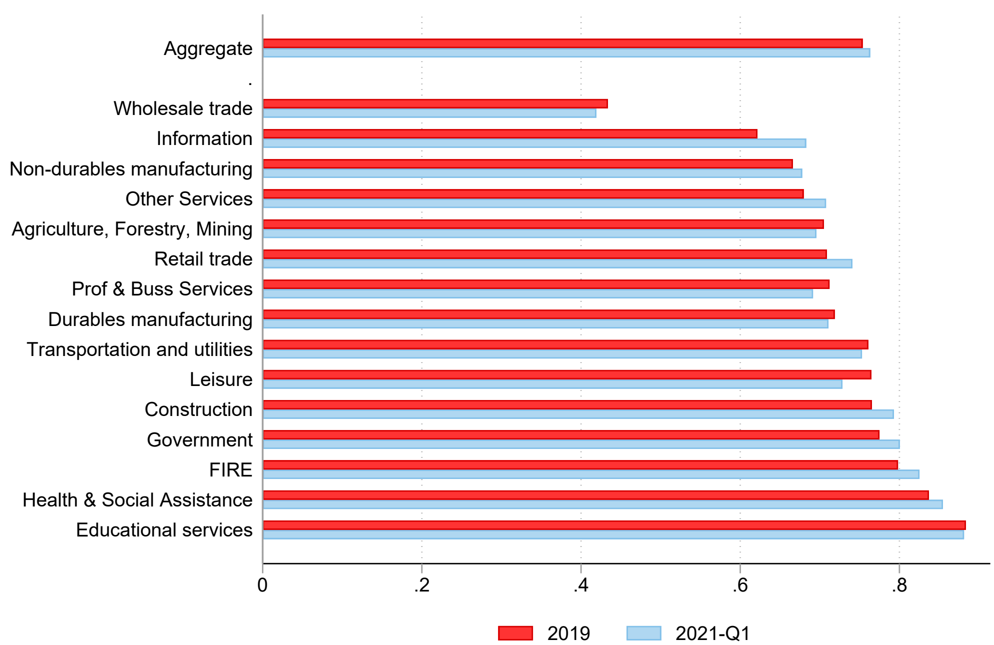
[11]In each case, we take the average across all months in the respective period. We do so because some sectors have low coverage in the CPS, and averaging across months helps correct for the small sample. For the same reason, we also group some groups of similar sectors together. These are: Finance, Insurance and Real Estate and Leasing (FIRE); Arts and Entertainment and Accommodation and Food Services (Leisure); Agriculture and Forestry and Mining (Agriculture and Mining).

[12]Source: California Policy Lab, December 8th Analysis of Unemployment Insurance Claims.

Figure 3: Sector stayers



(a) 2021-H2



(b) 2021 Q1, employed only

Notes: The figures show the share of workers employed in the same sector where they were employed a year earlier. In the top panel, the sample also includes individuals who exit into non-employment; in the bottom panel, it only includes employed workers. The bars show averages across all months for the respective period (2021-H2 includes May-August 2021). Some sectors have been grouped due to small sample size. Source: CPS.

ticular, policy reports from the California Policy Lab[13], using administrative evidence from unemployment insurance data from California, show that 68% of UI claimants in 2020Q2 had returned to the same industry a year later. More interestingly, this share was almost identical for both Accommodation and Food Services (65%) and for the Professional, Science and Technology sector (64%), even though these were two industries with diametrically opposite outcomes in the initial COVID-19 shocks.

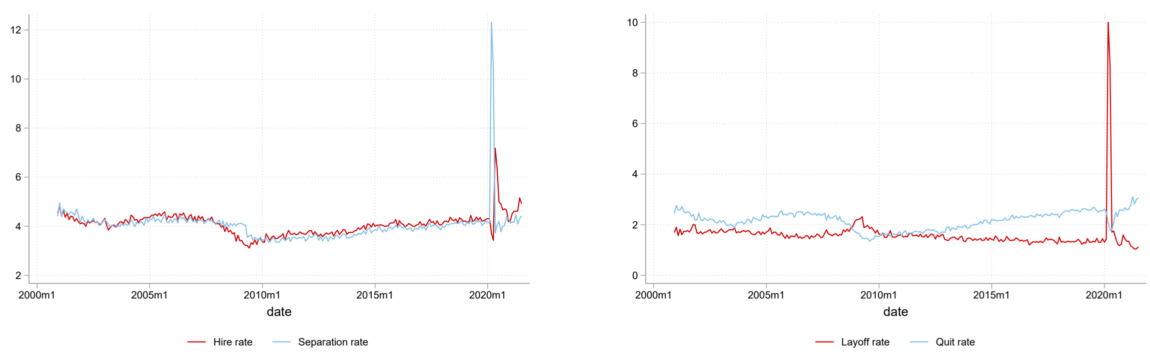
3.2 Hires and separations

We now consider hires and separations data from JOLTS. Figure 4-a shows seasonally adjusted sectoral hire and separation rates for the non-farm private economy.

Figure 4: Churn rates

(a) Hire and Separation rates

(b) Layoff and Quit rates



Notes: The figures show hires and separations for the non-farm private sector, split by firm size (number of employees). Data come from JOLTS. The hire and separation rates are defined as hires or separations over employment, multiplied by 100. The levels figures are plotted in square root scale.

Hires fell a lot in April 2020 relative to February in absolute terms, though they moved little relative to employment, due to a large denominator effect. Separation rates and levels more than doubled. Hires spiked up and separations collapsed in May 2020 once lockdowns were lifted, and by the end of the year they were similar to pre-COVID levels, despite employment being substantially lower (although separations were still lower, so the net increase in employment was still larger). Hires picked up steam further as the recovery broadened, along with the proliferation of vaccines in 2021, and employment still substantially lower than pre-pandemic. Separations have also been somewhat higher than historical averages in 2021.

[13]Source: California Policy Lab, ibid.

While the recovery of the aggregate economy in 2021 could account for the increase in the hiring rate, an elevated separation rate could indeed indicate an increase in churn. The total separation rate, however, is masking a steep rise in quits, as large numbers of US workers were quitting employment in the Spring and Summer of 2021. Figure 4-b shows separations split into layoffs and quits.[14] The average quit rate in 2021Q2, at 2.7%, was the largest recorded since JOLTS started in 2000. This can reflect both the strength of the labor market, as vacancies were also at record highs during the same period, while there is anecdotal evidence that workers are rethinking career trajectories (Furman & Powell 2021). Layoffs, on the other hand, have been trending lower; for the last three months of the sample (May-July 2021) they averaged 1.1%, over a third lower than the 1.6% average of the 2001-2019 period. Firms are still filling positions lost due to the pandemic, with employment 5 million lower than February 2020. Indeed, the layoff rate has fallen precisely in the sectors that experienced large losses due to the pandemic recession; the correlation of the change in the layoff rate (relative to historical standards) and log change in employment relative to February 2020 is 0.61.[15]

Finally, aggregate hires may still mask important differences in the cross-section that could indicate reallocation. Newly available size class data by JOLTS can shed light on this. Figure 5 shows seasonally adjusted sectoral hire and separation rates and levels for the non-farm private economy, by firm size (the levels are in square root scale), at different points of the pandemic era.

For small and medium firms, hires resumed their pre-COVID levels relatively quickly, after rising during summer 2020 following huge spikes in separations. In 2021, hires for these firms picked up considerably, and they seem to be largely driving the employment recovery. The pickup for the smallest firms is also consistent with evidence of a surge in new business applications, disproportionately found in internet sales[16].

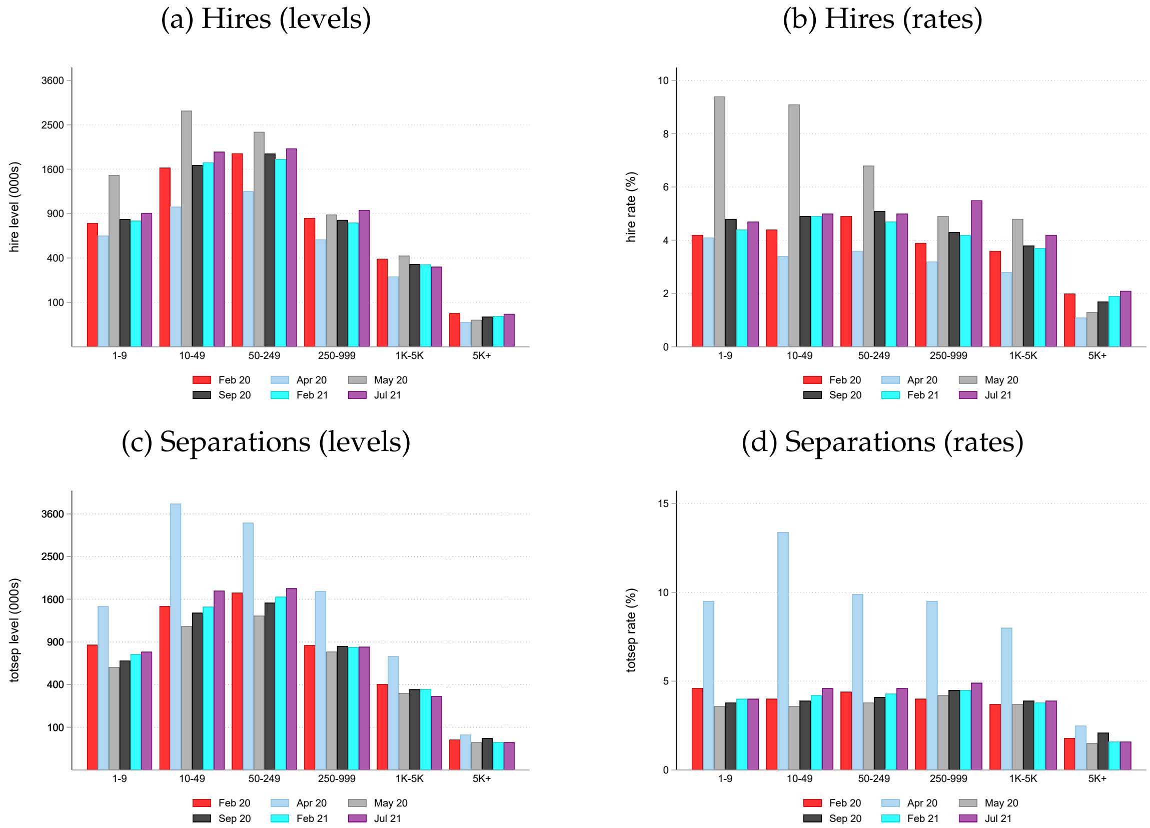
Throughout this period, and given the tighter borrowing constraints small firms faced (particularly in the earlier stages), one would expect increased hiring from larger firms (of the type detailed in the anecdotal evidence mentioned in Barrero et al. (2020) and this paper), who take advantage of the recession and try to expand their market shares. The data shows that while separations for these largest firms (over 5,000 work-

[14]Figure 4 in fact includes, in addition to layoffs and quits, other separations, which include retirements, deaths, exits due to disability, and transfers to another location. These are an order of magnitude lower than layoffs and quits, and have not risen appreciably.

[15]See also figure 10 in the appendix.

[16]See here.

Figure 5: Hires and separations by firm size, 2020-2021

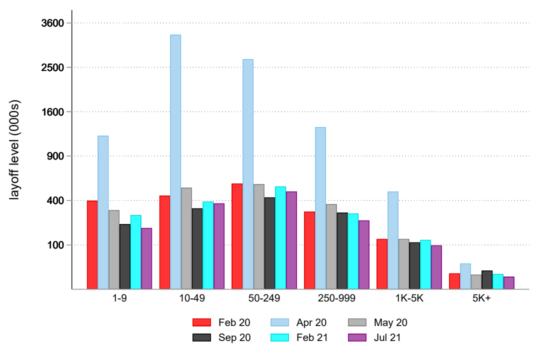


Notes: The figures show hires and separations for the non-farm private sector, split by firm size (number of employees). Data come from JOLTS. The hire and separation rates are defined as hires or separations over employment, multiplied by 100. The levels figures are plotted in square root scale.

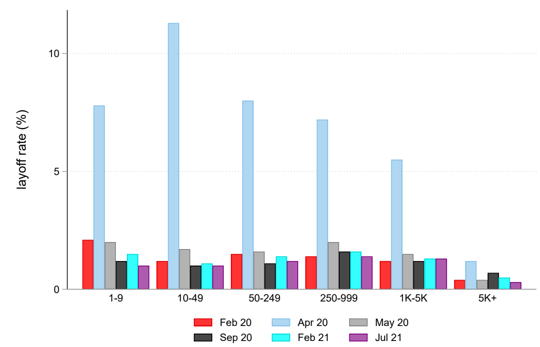
ers) were barely affected as a result of the pandemic, their hiring in fact fell and only reached its pre-pandemic levels by Summer 2021. It is well-known that a disproportionate fraction of hires comes from young firms, so a smaller contribution from the largest firms is to be expected. Note also that this pattern of increasing churn for small firms immediately after a large shock was also present after the Lehman shock, as shown by Moscarini & Postel-Vinay (2016). On the other hand, we know from the literature that smaller firms grow faster in recoveries, but larger one grow faster in tight labor markets (through poaching); as Summer 2021 is the time when labor market tightness (as conventionally measured by unemployment over vacancies) had reached pre-pandemic level, slower growth of the larger firms until then was to be expected. The upshot is that the data does not seem to suggest heightened levels of reallocation towards the largest firms.

Figure 6: Layoffs and quits by firm size, 2020-2021

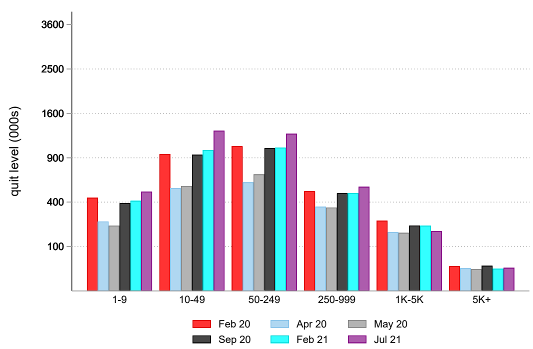
(a) Layoffs (levels)



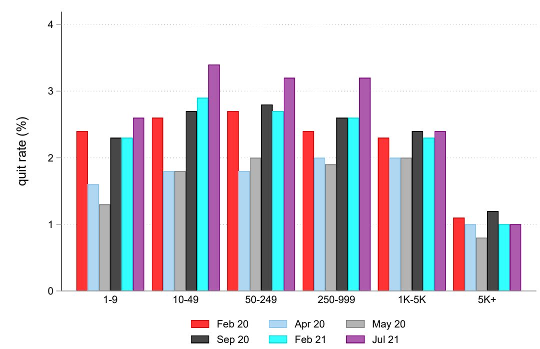
(b) Layoffs (rates)



(c) Quits (levels)



(d) Quits (rates)



Notes: The figures show hires and separations for the non-farm private sector, split by firm size (number of employees). Data come from JOLTS. The hire and separation rates are defined as hires or separations over employment, multiplied by 100. The levels figures are plotted in square root scale.

Figure 6 shows the breakdown of separations into layoffs and quits by firm size. The reduction in the layoff rate in 2021 is driven primarily by the smaller firms, so it is possible some of this is due to composition effects, through new firms entering. For firms with over 250 employees, layoff rates in July 2021 were at pre-pandemic levels or higher. Similarly, the elevated quit rate is also concentrated at small and medium firms.

Accounting for where these quitters go is beyond the scope of this paper. We note, however, that our results show that workers seems to move out of their sectors and occupations, as well as to other jobs in general, in reasonably similar rates as previously. The situation is much the same when looking across sectors. This idea of workers mostly moving to the same sector is strengthened when considering the correlation between job losses between February and April 2020, and job gains since then, is over 99%. Combined with the fact that the employment-to-population ratio, while still at historical lows, is rebounding quickly, there is enough evidence to suggest movement of workers is mostly taking place across firms, not sectors or occupations.

Overall, the results of the preceding analysis do not point to a clear reallocation wave. First, expected reallocation measures have come down substantially since the Spring of 2020, suggesting a reevaluation of initial arguments signaling major reallocation. CPS data show that occupational or sector switching stayed at normal levels, across different definitions. JOLTS data point to an increase in the hire rate in 2021, as firms rebuild their stock of labor; separations are also elevated, which could indicate higher churn. However, a large part of the change in separations reflect an increase in quits, which are at historical highs. Data by firm size indicate most of the action is coming from small firms; in particular, the purported increase in hires from large firms who tried to exploit the pandemic shocks is not borne out by the data.

4 Mismatch unemployment

An indirect way of studying the magnitude of the reallocation shock is by examining the extent to which unemployment is frictional. A large reallocation shock implies that workers need to be shifted across sectors and occupations, but matching frictions can slow down this reallocation, creating mismatch unemployment over the short-run. Determining the level of mismatch unemployment can have important implications about the scope of policy action. If a large fraction of unemployment is due to mismatch, then demand-side policies (fiscal or monetary) may be ill-advised, and supply-side policies (such as employment assistance or training programs) are more appropriate.

We estimate the extent to which the high levels of unemployment during the pandemic are due to mismatch, using the framework of Sahin et al. (2014). In their multi-sector version of the canonical search and matching model, matching frictions lead to a mismatch between vacancies and jobseekers across sectors, which impedes the aggregate job-finding rate and leads to a higher unemployment rate. By comparing actual unemployment u with a counterfactual unemployment u^* from a planner who distributes workers across all vacancies, one can gauge the portion of unemployment that is exclusively due to mismatch. This framework, which casts mismatch (and mismatch unemployment) as deviations from an optimal allocation, is ideally suited to the exercise at hand, as we try to estimate the extent to which frictions are preventing reallocation of workers from declining to booming sectors.[17] The indicator measures mismatch across, not within sectors, and as such the results should be benchmarked relative to pre-pandemic levels. The measure also ignores employed individuals seeking employment (through on-the-job search); this is unlikely to have mattered crucially during the early parts of the pandemic, but may have become more important in recent months.

We present here the basic intuition, maintaining the original notation of Sahin et al. (2014). For more details, see Sahin et al. (2014). The economy contains a set I of distinct labor markets; unemployed workers search for jobs in one sector only, and labor markets are frictional, with matches determined by the sectoral matching function:

$$h_{it} = \Phi_t \phi_{it} \nu_{it}^{\alpha} u_{it}^{1-\alpha}, \tag{1}$$

where Φ_t and ϕ_{it} are aggregate and sectoral matching efficiency parameters, respectively, ν_{it} are vacancies, u_{it} unemployed workers seeking jobs, and h_{it} are hires, for sector i in period t. As such, different labor markets are allowed to have different matching efficiencies. Parameter α is between 0 and 1 and is the vacancy share, common across all sectors. The mismatch index $M_{\phi,t}$ is then given by

$$M_{\phi,t} = 1 - \frac{h_t}{h_t^*} = 1 - \sum_{i=1}^{I} \left(\frac{\phi_{it}}{\bar{\phi}_t}\right) \left(\frac{\nu_{it}}{\nu_t}\right)^{\alpha} \left(\frac{u_{it}}{u_t}\right)^{1-\alpha}, \tag{2}$$

with $h_t^* = \bar{\phi}_t \Phi_t \nu_{it}^{\alpha} u_{it}^{1-\alpha}$ and $\bar{\phi}_t = \left[\sum_{i=1}^{I} \phi_{it}^{\frac{1}{\alpha}} \left(\frac{\nu_{it}}{\nu_t}\right)\right]^{\alpha}$. h_t^* is the optimal number of hires, and $\bar{\phi}_t$ is an aggregator of sectoral matching efficiency parameters, weighted by sectoral vacancy shares. Note that the planner can only move workers across markets, but is still bound by the within-market matching friction.[18] As Sahin et al. (2014) note, the index measures the fraction of hires lost due to mismatch. A planner would eliminate it by placing unemployed workers across sectors by vacancies. Intuitively, a higher covariance of vacancies and unemployed workers (at the sector-time level) would imply a lower mismatch index.[19]

[17] One caveat is that our data only allow construction of sectoral mismatch indices.

[18] In other words, the planner cannot eliminate all unemployment, only that which arises from misallocation of searchers across sectors. This setup allows one to capture frictional unemployment.

[19] Sahin et al. (2014) prove that i) the index is between 0 and 1; ii) it is invariant to aggregate shock shifting total vacancies and unemployed but leaving the shares across sectors unchanged; and iii) it rises in disaggregation, and so comparisons should be made keeping disaggregation fixed.

Allowing productivity z_{it} and job destruction rates δ_{it} to be heterogeneous across sectors, let $x_{it} = \phi_{it} z_{it}/[1-\beta(1-\delta_{it})]$, where β is the discount rate. This measure, which Sahin et al. (2014) call overall market efficiency, is the destruction-rate and productivity adjusted matching efficiency of the sector. Under heterogeneity, the planner wants to maximize output, and so sectors with higher productivity and lower destruction rates are given higher weights. The index becomes

$$M_{xt} = 1 - \sum_{i=1}^{I} \left(\frac{\phi_{it}}{\bar{\phi}_{xt}}\right) \left(\frac{\nu_{it}}{\nu_t}\right)^{\alpha} \left(\frac{u_{it}}{u_t}\right)^{1-\alpha}, \tag{3}$$

where $\bar{\phi}_{xt} = \sum_{i=1}^{I} \phi_{it} \left(\frac{x_{it}}{\bar{x}_t}\right)^{1/\alpha - 1} \left(\frac{\nu_{it}}{\nu_t}\right)$ and $\bar{x}_t = \left[\sum_{i=1}^{I} x_{it}^{1/\alpha} \left(\frac{\nu_{it}}{\nu_t}\right)\right]^{\alpha}$. If we instead assume homogeneous matching efficiency, productivity, and destruction rates across sectors, then the index simplifies to $M_t = 1 - \sum_{i=1}^{I} \left(\frac{\nu_{it}}{\nu_t}\right)^{\alpha} \left(\frac{u_{it}}{u_t}\right)^{1-\alpha}$. We also consider, in line with Sahin et al. (2014), mismatch indices $M_{\delta,t}$, and $M_{z,t}$, where heterogeneity is only in the form of destruction rates and productivity, respectively (in addition to unemployment and vacancies).

Focusing now on the homogeneous case (M) for brevity, from (2), the job finding rate can be written as

$$f_t = 1 - \frac{h_t}{u_t} = (1-M_t)\Phi_t \left(\frac{\nu_t}{u_t}\right)^{\alpha}. \tag{4}$$

Defining f_t^* as the finding rate when $u_t = u_t^*$ and s_t as the separation rate, the dynamics of u_t^* are defined by $u_{t+1}^* = s_t + (1 - s_t - f_t^*)u_t^*$. The difference between u_t and u_t^* gives mismatch unemployment. Notice that

$$f_t^* = \left(\frac{\nu_t}{u_t}\right)^{\alpha} = f_t \underbrace{\frac{1}{1-M_t}}_{\text{direct}} \underbrace{\left(\frac{u_t}{u_t^*}\right)^{\alpha}}_{\text{feedback}}. \tag{5}$$

The optimal finding rate is related to the actual finding rate through two terms. The "direct effect" is simply related to the presence of mismatch. However, with lower mismatch and a lower overall unemployment, it becomes easier for unemployed workers to meet a vacancy, further reducing unemployment and giving rise to this "feedback" effect. Sahin et al. (2014) argue that the presence of the feedback effect implies that mismatch unemployment may remain high for some time after mismatch has fallen, due to delays in the reabsorption of unemployed workers.

We calculate the five measures for the period January 2012-June 2021, except for those with heterogeneity in destruction rates ($M_{x,t}$ and $M_{\delta,t}$), where data stop at December 2020. Results are given in figure 7, where the left panel shows the different mismatch indicators, and the one to the right shows the associated mismatch unemployment rates. For clarity, we show, in the top panel, the baseline (M_t) and measures allowing for heterogeneity in matching efficiency ($M_{\phi,t}$ and $M_{x,t}$), and in the bottom one the ones with homogeneous matching efficiency ($M_{\delta,t}$ and $M_{z,t}$).

Consider first M_t and $M_{\phi,t}$ in fig 7, the measures without heterogeneity and with matching efficiency heterogeneity only. After a slowly diminishing trend after the Great Recession, mismatch rose sharply at the start of the pandemic (shaded area), rising by over 50% relative to February, before falling sharply once the first part of the shock passed and employment started to recover. The further pickup in economic activity in early 2021 led to a further reduction in both measures, which, by Summer 2021, were back to pre-pandemic levels, and in line with historical standards. The measure with productive heterogeneity only, $M_{z,t}$, behaves similarly. We see instead a different behavior for $M_{x,t}$ and $M_{\delta,t}$, where mismatch falls sharply on impact. As Sahin et al. (2014) stress, when allowing for heterogeneity in productivity, the planner maximizes the present discounted value of output, and not necessarily hires, and so in principle optimal hires may be lower than equilibrium hires, resulting in negative mismatch. A similar reasoning holds for the case where destruction rates are allowed to be heterogeneous. The nature of the shock in 2020Q2[20] when output exhibited its sharpest monthly reduction on record, led to large swings in these measures, because the correlation of $\delta_{i,t}$ with ϕ_i and $x_{i,t}$ fell substantially. In any case, the measure recovered to levels close to the other measures once the initial anomaly passed, and overall all measures show a very similar qualitative behavior, indicating little to no change in overall mismatch by late 2020.

Turning over to mismatch unemployment, let mismatch unemployment be given by $\hat{u} = u - u^*$, with appropriate subscripts for each measure. We see that estimated mismatch unemployment pre-pandemic was quite similar across measures, but diverged since. For each measure, mismatch unemployment dipped initially, likely due to the initial fall in vacancies, but rose thereafter. The rise was modest for all measures, how-

[20]Since output data are quarterly, this fall is also apportioned to May and June.

ever. Mismatch unemployment for the measures without heterogeneity in destruction rates ($\hat{u}, \hat{u_\phi}$, and $\hat{u_z}$) rose by around 0.4-0.5 percentage points (pp) relative to their pre-pandemic average by summer 2020 (measured from 2019 to February 2020), but has since fallen to roughly 0.3-0.4pp relative to the pre-pandemic era. As excess unemployment due to the pandemic (relative to February 2020) has fallen from highs of over 10% to 2.4% by June 2021, the share of mismatch unemployment out of total has slightly risen, but mismatch remains a marginal contributor to overall unemployment; for M_ϕ, which exhibits the largest mismatch, $\hat{u_\phi}$ accounts for 14% of total and less than a fifth of the increase. It is also important to note that mismatch unemployment has remained higher far longer than mismatch itself, confirming the importance of the "feedback" mechanism.

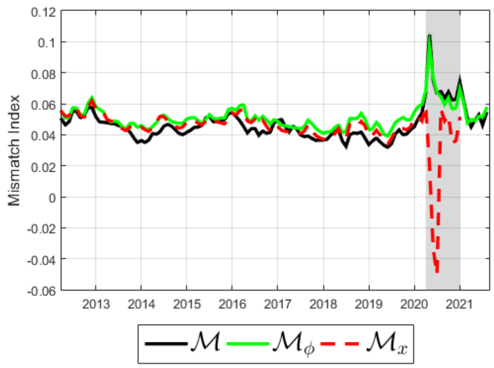
The measures that take into account heterogeneity in destruction rates, $\hat{u_x}$ and $\hat{u_d}$, after the initial fall to slightly negative territory described previously, rose to levels very close to pre-pandemic by the end of 2020, and much less than the other measures, though $\hat{u_d}$ was almost 0.2pp higher at the end of the sample. Recall that $\hat{u_d}$ allows only for heterogeneity in destruction rates, $\hat{u_z}$ only for productivity heterogeneity, and $\hat{u_x}$ for both, as well as matching efficiency heterogeneity. We see that $\hat{u_x}$ is lower than the other two measures, which is because of the negative covariance between matching efficiency and destruction-adjusted productivity, which, while smaller than in the initial shock, has persisted until the end of 2020.

The analysis has so far implicitly assumed constant matching efficiency for each sector. Given the size of the shock, and to allow more flexibly for the possibility that a reallocation shock may have changed matching efficiency differentially across sectors, it may be useful to also allow for matching efficiency ϕ to be different during the pandemic, for those measures incorporating matching heterogeneity ($M_{\phi,t}$ and $M_{x,t}$). To do so, we estimate matching functions using the procedure outlined in Sahin et al. (2014), with a separate slope parameter for the pandemic period. The results are given in figure 8, together with the simple baseline measure M_t for comparison purposes. We see that the differences between M_t and $M_{\phi,t}$ are somewhat larger pre-pandemic; mismatch unemployment with matching heterogeneity, in particular, is almost always about 0.2pp higher than the baseline measure, but the trends remain very similar throughout the sample, and this does not change in the pandemic.

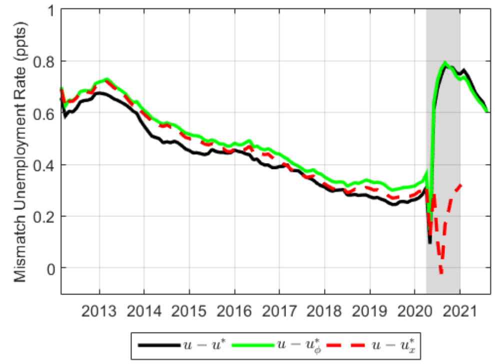
Overall, it appears that little of the increase in unemployment can be explained by mismatch. As the recovery broadens, it is likely that mismatch will account for an

Figure 7: Mismatch

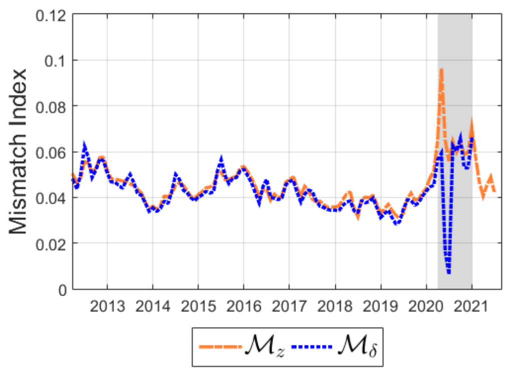
(a) Mismatch index - heterogeneous ϕ_i



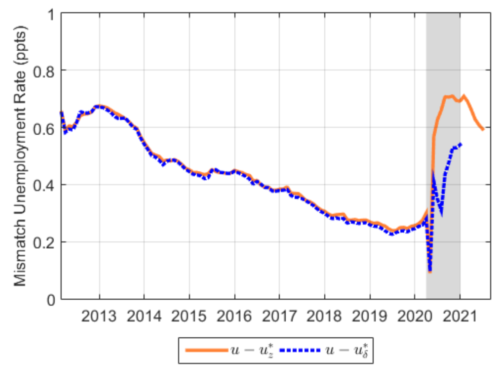
(b) Mismatch Unemployment- heterogeneous ϕ_i



(c) Mismatch index - homogeneous ϕ_i



(d) Mismatch Unemployment - homogeneous ϕ_i



Notes: The figures show the mismatch index (left-hand side) and the implied mismatch unemployment (right-hand side), according to the method of Sahin et al. (2014). The sample is January 2012-July 2021.

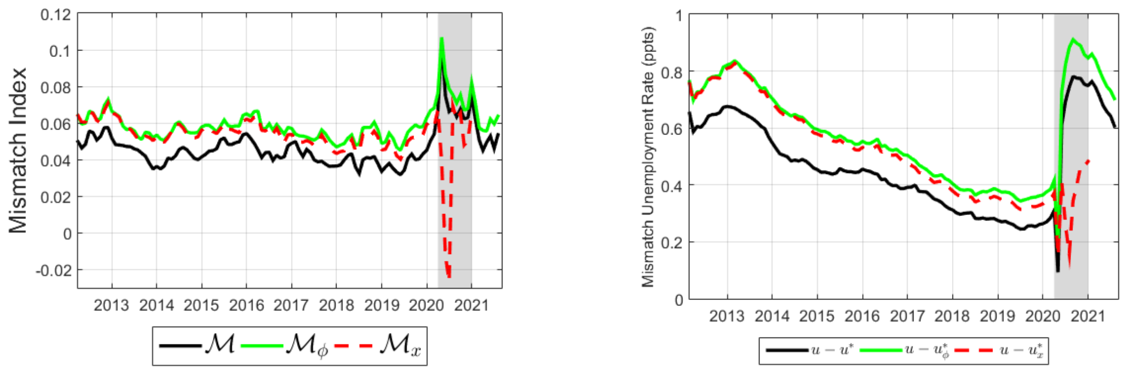
ever larger share of total unemployment, but the evidence so far suggests that frictions potentially slowing down the labor market adjustment to the shock have not been a large driver of unemployment during the pandemic recovery.

5 Structural identification of reallocation shocks

We directly examine for the possibility of a job reallocation shock in driving the aggregate labor market patterns during the pandemic, through the lens of a Bayesian SVAR model with sign restrictions. Such models are often used to study the effects of tech-

Figure 8: Mismatch unemployment - varying matching efficiency

(a) Mismatch index- varying ϕ_i (b) Mismatch Unemployment - varying ϕ_i



Notes: The figures show the mismatch index (left-hand side) and the implied mismatch unemployment (right-hand side), according to the method of Sahin et al. (2014). The sample is January 2012-July 2021.

nology on labor, where a positive technology shock is typically assumed to have pro-growth and disinflationary effects.

The macro-econometric literature has widely considered the role of technological changes on growth, productivity and employment. Galì (1999), Christiano et al. (2003), Uhlig (2004), Francis & Ramey (2005), Dedola & Neri (2007), Canova et al. (2010) and Mumtaz & Zanetti (2012) use different identification strategies to measure the effects of neutral or investment-specific technology shocks in the economy. The former type of shock refers to exogenous changes in TFP that equally affect the marginal productivity of capital and employment in the aggregate production function. The investment-specific technology shock, instead, is defined as directly affecting the price of investment, especially of ICT (information and communication technology) capital. That is, higher efficiency in producing capital goods leads to stronger investment patterns in machinery and equipment, which is indirectly followed by higher economic growth and stronger labor demand. A feature of our identification approach is that we aim at identifying a number of structural shocks which is equivalent to the number of our endogenous variables in the VAR.

Job reallocation shock In this paper, we impose a novel identification scheme, whereby we differentiate between two types of technology shocks: a standard factor neutral aggregate supply shock (ASTech) and a reallocation shock (ASJRe). We introduce job reallocation as a shock that captures the efficiency gains from the current capital and labor allocation via an increase in job turnover, measured by higher hiring and destruction rates. Output responds positively to both types of shocks, but they differ substantially in their labor market effects. While ASTech is assumed to raise wages and reduce layoffs, ASJRe induces churn in the labor market: we assume it raises both hires and layoffs, as well as unemployment.

Differently from other technology shocks, job reallocation shocks are expected to weaken labor demand and lead to an on-impact surge in the unemployment rate. This is because it takes time to create new jobs when firms decide to switch jobs away from certain occupations/tasks and to create new ones with a higher embedded technological content. The reallocation is thus expected to enhance productivity and will support higher job posting. As displaced workers will face adverse labor demand conditions and higher mismatch in the labor market, a job reallocation shock which has positive effects on output is likely to have non-positive effects on wages.[21] In general, the reaction of price inflation is not pinned down as it is negatively affected by the increase in efficiency from job reallocation, while higher marginal costs could arise from investments in capital goods and high-skilled workers.

A job reallocation shock differs from a job matching efficiency shock because – given similar responses of job flows - the response of the unemployment rate and wages will be different. An improvement in matching efficiency will ameliorate the matching and hiring process and decrease unemployment, while job reallocation will lead to a temporary increase in the unemployment rate. Regarding wages, while the gains from higher matching efficiency will partly be shared between employers and employees, the job reallocation effect is expected to exert temporary downward pressure on wages.

Neutral shock In the standard Mortensen & Pissarides (1994) model, an aggregate (neutral) technology shock benefits all workers. The endogenous probability of separation decreases because the value of the marginal job benefits from a right-shift of the productivity distribution. At the same time, the response of the job finding rate depends on the degree of price flexibility in the economy. In a New-Keynesian model with a high degree of price stickiness, output does not adjust enough after a neutral technology shock to accommodate an increase in employment, and the job finding rate may

[21] Our baseline set of identification restrictions does not constrain the on-impact effect of ASJRe on wages.

Table 1: Matrix of Sign Restrictions

	Shock					
Variable	AggDem	ASTech	ASJRe	WagBag	MatEff	LabSup
IndPro	+	+	+	+	+	+
PCEy	+	-		-	-	
Wages		+		-		-
URate	-		+	-	-	+
Hires	+		+		+	
Layoffs	-	-	+	-	+	-

Notes: The table shows the sign-based identification restrictions imposed by our SVAR framework. A "+" indicates that we restrict the sign of the on-impact response of the variable to the shock to be positive. Similarly for the negative "-" sign. An empty cell indicates that no restriction has been imposed. *IndPro* refers to Industrial Production, *PCEy* to personal consumption expenditure inflation, *Wages* to Atlanta Fed measure of nominal wages, *URate* to the unemployment rate. Similarly, *AggDem* refers to Aggregate Demand, *ASTech* to the neutral technology shock, *ASJRe* to the job reallocation shock, *WagBag* to the wage bargaining shock, *MatEff* to the matching efficiency shock, and *LabSup* to the Labor Supply shock.

decrease. In the class of flexible price models, instead, the response of output is stronger and that leads to higher labor demand and higher job finding rate. In this latter case, the combined effects from the job finding and separation rates clearly identify the sign of the employment response. In general, given the uncertainty about the sign of the response, we keep the sign of the identification restriction of a technology shock on the unemployment rate and hires unconstrained.

Other shocks Canova et al. (2010) find that neutral technology shocks explain only a small portion of labor market fluctuations (measured as per-capita hours) and a much larger portion of output fluctuations. Canova et al. (2013) instead argue that neutral shocks increase unemployment and explain a substantial portion of its volatility, while Foroni et al. (2018) find an important contribution from both labor supply shocks and wage bargaining shocks. We thus augment our identification structure with additional shocks that are more tailored to explain fluctuations in the labor market.

We include aggregate demand, labor supply, matching efficiency and wage bargaining shocks to complete our model. Anzoategui et al. (2019) provide a rationale for looking at aggregate demand shocks, as they may lead to more persistent effects on output and labor market variables, which could help to explain the fallout from the Global Financial Crisis (GFC). Labor supply shocks are also relevant in view of the stark contraction of labor force participation after the GFC. This decline, which blurs developments in the unemployment rate is, together with the wage bargaining shock, relevant to explain relatively moderate wage dynamics during the recovery (Daly & Hobijn (2013), Yellen (2014)). In the context of the COVID-19 pandemic shock, the labor supply shock (LabSup) is ideally suited to capture the direct effects of lockdowns and movement restrictions on aggregate variables. We restrict LabSup to have a positive sign on IP, negative on wages, and positive on unemployment. The rationale is that higher labor supply (entry from inactivity) increases the labor force and labor incomes; unemployment mechanically rises as it takes time for new entrants to be absorbed, while wage fall due to increase slack. We also introduce a negative sign on layoffs, which is necessary to separately identify LabSup from ASJRe. The intuition is that the expansionary effect of the shock will tend to reduce layoffs, ceteris paribus. In turn, the matching efficiency shock (MatEff) relates to shifts in the Beveridge curve which are affecting by exogenous changes in the aggregate matching function. Consolo et al. (2021) find that a job matching efficiency shock is quantitatively important to explain fluctuations in the unemployment, separation and job finding rate. MatEff raises churn and reduces inflation, just like ASJRe, but reduces unemployment by improving matching.

Estimation We estimate a six-variable model for the US economy in monthly frequencies. Our model includes industrial production, inflation, wage growth, unemployment, layoffs, and hires. We estimate the model using a Bayesian SVAR model with six lags, using the methodology of Arias et al. (2018).[22] We use a flat (normal-diffuse) prior with standard hyperparameters. The identification process is based on sign restrictions for the impact period, and we use 1000 draws for the burn-in sample, and 2000 draws for the estimation sample. All shocks and respective sign restrictions are summarized in Table 1. Figure 20 shows the impulse responses of all variables for each of the shocks.

Results We provide results across all identified shocks to gauge their respective relevance for business cycle fluctuations. We then look at the recent COVID crisis to see which class of shocks has been more important.

Figure 19 summarizes, for each of the variables in our VAR model, the share of the

[22] We use the BEAR 5.0 Toolbox of Dieppe et al. (2016).

volatility explained by each shock. Structural shocks drive endogenous variables in different ways. This implies that the conditional correlation among endogenous variables may get stronger or weaker depending on the main business cycles forces. Technology and job reallocation shocks appear to be mostly relevant for wages; the share of variance explained by these two aggregate supply shocks is limited for the rest of the endogenous variables – including output. The evidence in the literature is rather mixed on the issue, which to some extent can be explained by differences in sample period, variable choice, and shocks. Closest to ours is the setup of Foroni et al. (2018), who also include a demand shock, and also find a relatively small role of neutral technology shocks for the labor market.

Figures 13-18 provide the historical decomposition of the shocks for each endogenous variable, separately for the full sample, and the sub-sample since 2018. We focus our discussions on how the shocks affected the endogenous variables during the COVID shocks, distinguishing between initial effects, when output collapsed, and longer-term effects during 2021, when the economy made up for the pandemic shock and recovery accelerated. The initial effects would primarily manifest in how firms adapted to lockdowns and the switch to work from home, while the recovery phase should reflect higher efficiency from adoption of new technologies and resource reallocation, together with a pickup in inflation associated with supply shortages.

During the initial phase, the dominant factors behind the fall of Industrial Production were the collapse in AggDem and, to a somewhat lesser extent, a negative contribution from ASTech, reflecting supply bottlenecks and lockdowns. This is consistent with the idea that supply shocks affecting specific sectors can affect demand and hence output even in other sectors, through sectoral complementarities, as workers for one sector are consumers for another; see Guerrieri et al. (2020), Woodford (2020) for formal derivations of these arguments. The other shocks had smaller effects, with negative contributions from LabSup and WagBag; the first also reflects supply bottlenecks and lockdowns, while the latter likely reflects the role of wage rigidities (see below). There were small positive contributions from ASJRe and MatEff but were too trivial to matter. As the initial effect receded and movement restrictions subsided, industrial production rose, driven by all shocks, with the largest contributions by AggDem and ASTech, particularly later in the sample, as restrictions were lifted and vaccinations allowed the opening of contact-intensive activities. Here there is a larger role for a reallocation shock in driving the growth of production, though the effect is smaller, and is not exceptionally high by historical standards, as there was an important contribution in earlier episodes as well.

For inflation, the results are quite similar (figure 14). The bulk of the variation in the initial shock is explained by aggregate demand on the negative side, and ASTech on the positive side. This is a fairly straightforward and classic result, and consistent with most narratives of the pandemic. Conversely, the large increase in inflation towards summer 2021 is primarily driven by AggDem, even though the other shocks also contribute positively. ASJRe also has a positive contribution towards the end of the sample, but much smaller than AggDem, and also not especially large relative to other episodes.

Moving to the labor market, we first look at layoffs (figure 15). The model ascribes the initial steep increase to all shocks, with the largest contributions coming through AggDem, ASTech and WagBag. This is again consistent with the collapse of aggregate demand, stay at home orders and supply bottlenecks. The role of wage bargaining in this context is understood through nominal rigidities in the face of a steep reduction in production, which prevented matches from being preserved. This inefficient labor shedding aspect of the pandemic has been documented also in Giupponi & Landais (2020) and Petroulakis (2020). The reduction in layoffs in 2021 was initial driven by AggDem, and then by a combination of all shocks. In 2021Q2, ASJRe had a positive contribution to layoffs, which could reflect the reopening of large parts of the economy.

AggDem and WagBag were also the major driver of the initial fall in hires, but their subsequent rise was the result of positive contributions from essentially all variables, throughout the pandemic episode. The contribution of ASJRe was at its largest in 2021Q2, just as with layoffs. And while the overall hire rate has been exceptionally large by historical standards, due to the very large initial reduction in the employment pool and the need to fill vacancies, the relative contribution of reallocation to this elevated hire rate does not stand out. In the hiring slump after the GFC, in the expansion of the mid-2010s, as well as in the pre-GFC period, there is always a meaningful role for reallocation in driving hires. Overall, ASJRe does play a role in driving churn, but it is minor relative to the other shocks, despite a pickup late in the sample. As a result, ASJRe has a relatively minor role in the evolution of unemployment, especially in the early phase of the pandemic, when unemployment was at all-time highs, and any effect should have been particularly strong then. The role of ASJRe is stronger in 2021Q2, where it has a positive effect; note that this is consistent with the "feedback" effect of Sahin et al. (2014) analyzed in the mismatch section. Episodes of high unemployment may result in prolonged higher mismatch unemployment, even if mismatch itself has subsided, due to delays in filling vacancies. The same argument explains the role of MatEff, which exerts a positive effect on unemployment when it peaks, and then when in 2021Q2.

For completeness, we also consider wages. In the short run, both aggregate and labor market-specific shocks play a role for wage growth, while over the long run wages are mostly driven by aggregate shocks, AggDem and ASTech. In the pandemic period, the main drivers were AggDem, WagBag and LabSup shock. The positive contribution of WagBag reflects the role of nominal downward wage rigidity in preventing a fall in nominal wages in the face of the spike in unemployment (see Abbritti et al. 2021 and Grigsby et al. 2021). LabSup also played a very important role in wage formation as the participation margin was a very important channel of labor market adjustment during the pandemic because both the lockdown restrictions and the degree of home working were heterogeneous across sectors, firms and worker types.

5.1 Further sensitivity checks

We test the sensitivity of our results to our specification and data choices in a number of ways. First, instead of our baseline choice of a normal-diffuse prior, we use the optimal prior selection procedure of Giannone et al. (2015). This approach treats the informativeness of these priors as additional hyperparameters, and estimates these parameters by maximizing their posterior distribution under a flat hyperprior. The authors show that this is equivalent to maximizing the one-step ahead forecasting ability. Imposing this optimal prior selection prior has little effect on our results.

Second, we try different restrictions for the effect of ASJRe on wages and of LabSup on aggregate demand. In the former case, the sign is theoretically ambiguous, while in the latter, the restriction maybe redundant. We confirm that any relevant permutation has little bearing on the main results.

A final concern relates to the choice of the wage variable. The focus on continuing workers to correct for compositional effects may be a concern if the wages of continuing workers and new hires behave differently across the cycle. The literature remains quite mixed on this issue; Haefke et al. (2013) argue that wages of new hires respond strongly to productivity, and Hall & Milgrom (2008) that continuing workers are more insulated from cyclical shocks. On the other hand, Gertler et al. (2020) posit that this procyclicality is only relevant for job-to-job transitions, and reflects procyclical improvement in matches. They do not find excess cyclicality for hires from unemployment. We note that the vast majority of job losses in the initial COVID shock were temporary layoffs Hall & Kudlyak (2020), and it is likely that these workers were rehired at their previous wages. It is not possible to check this directly in a statistically meaningful way, but we repeat the SVAR exercises using wage growth for job switchers (instead of all continuing workers), and find little difference in the results.[23]

5.2 Accounting for the COVID shock

A well-known problem in estimating macroeconomic time series models which incorporate the pandemic era is that they include a few extreme observations for the early part of the episode. These outliers can seriously affect parameter estimation and bias results, and so the literature has suggested a number of methods to combat it. A popular approach is the one proposed by Lenza & Primiceri (2022), who treat the COVID-19 shock as an increase in volatility, and propose dividing the pandemic observations by some factor to be estimated; for parameter estimation, they argue that simply dropping the pandemic sample is sufficient. Neither of these approaches is suitable for historical decomposition, our main object of interest. Dividing the pandemic observations essentially implies shrinking down these observations so much that the historical decomposition is not possible. Dropping the pandemic sample is also not a solution, because, as Brinca et al. (2021) argue, the pandemic did likely lead to changes in responses to shocks, and so ignoring these changes, including in the lag structure (as the shock was persistent) may lead to biases in historical decompositions. In a different approach, Ng (2021) proposes to explicitly accounting for the pandemic shock by including monthly log differences of COVID cases as an exogenous variable in a VAR.

We adopt the pandemic priors method of Cascaldi-Garcia (2022), who combines elements of the two previous approaches. He proposes adding time dummies for the first six months of the pandemic, which amount to allowing for intercept shifts for that period, a procedure implemented in closed-form using the Bańbura et al. (2010) dummy

[23] The reason why it is not possible to check directly the wages of these individuals is the nature of the CPS rotating. CPS is a rotating panel, where workers are observed for four consecutive months, dropped for eight months, and then observed for another four consecutive months. Moreover, they only report wages in the fourth and eighth month of observation. As such, we can only capture 12-month wage growth for these workers only if the April 2020 was their 6^{th} or 7^{th} month. The sample remaining to complete this calculation (using the tools provided by the Atlanta Fed Wage Growth Tracker) is only a few dozen observations for each month, rendering precise estimation impossible.

observations method. Standard practice in BVAR estimation is to assume little is known about exogenous variables (including the constant), which are hence allowed to have very uninformative priors, with a very large shrinkage parameter (i.e. implying very low shrinkage). One complication in our context is that, with a large shrinkage parameter, the dummies will soak up all the variance for the pandemic months. We hence opt to also estimate our model with a lower shrinkage parameter for the time dummies.[24]

As our interest lies in describing the historical decomposition of the data, the decompositions without any adjustment remain our baseline results. We now present results with pandemic priors, in order to make sure the main conclusions remain robust. Results are shown in figures 21-26, for the whole sample, and the sample starting in 2018, as before. As expected, the pandemic shock, captured by the pandemic dummies and labelled "COVID" in the legend, accounts for a large share of movements across variables, especially for IP and the labor variables. Relative to the baseline results, the pandemic dummies eat away the contribution of AggDem, especially early in the COVID episode, but also from LabSup, especially for hires. Another difference lies in the contribution of MatEff for hires, as the impulse response is now stronger. Notice also that the pandemic dummies eat away at the contribution of AggDem to inflation in the latter part of the sample, when inflation started to take off, because their effect is so persistent.[25] In any case, the main conclusions stand: the reallocation shock is not an especially important driver of the labor market during the pandemic, especially in relation to its historical contribution.

6 Conclusion

In this paper, we critically examine the case for a pandemic-induced reallocation wave in the United States, taking a broad perspective. First, we consider direct evidence for CPS and JOLTS, focusing in particular on standard measures of churn, as well as movements by firm size. In the CPS, we show that there is no discernible uptick in the share of workers switching sectors or occupations, be it in the aggregate or in the cross-section. Other data corroborate that even workers who lost their jobs when the pandemic shock hit tend to be re-employed in the same sector a year later, in similar fashion as before the pandemic. From JOLTS, we find that the hire rate moved much less than the separation

[24]We thank Danilo Cascaldi-Garcia for helpful discussions on this issue.
[25]Note that this is likely due to base effects, which are unavoidable with an annual measure.

rate in the early stages, despite high unemployment; it rose later on, especially in 2021, in line with the pickup in the aggregate economy, but has also been accompanied by a reduction in layoffs.

We also do not find evidence of large hiring sprees for the very large firms, who were expected to gain substantially from the pandemic. Instead, and primarily until Summer 2021 (when the labor market had started to tighten substantially), we find evidence consistent with well-known patterns of cyclical behavior by firm size (Haltiwanger et al. 2018, Moscarini & Postel-Vinay 2012), with large firms contracting less in the initial shocks, but growing more slowly during the expansion. The absence of large movements for the largest firms could of course still be consistent with substantial reallocation within these firms (who for instance could increase their use of labor-saving technologies and workers in abstract tasks, at the expense of other employees), but it fails to reflect the popular narrative of massive hires by the largest firms. Taken together with the results of Barrero et al. (2020), these findings imply that reallocation may have yet to take off, but if it has, it is taking place within occupations and sectors.

We then take an off-the-shelf multisector search and matching model to examine whether mismatch unemployment rose as a result of the pandemic. A reallocation shock should have led to a large and persistent rise in mismatch unemployment (as a share of total), as workers move to new and growing sectors. We find little evidence to support this view; by all measures, mismatch unemployment has been less than 1 percentage point during the whole of the pandemic, accounting for 14% of total unemployment in February 2021, and less than a fifth of the total increase. Just like Sahin et al. (2014) show for the aftermath of the Great Recession, mismatch unemployment has not been an important factor for the pandemic recession either.

Finally, we look for evidence of a reallocation shock using a novel identification strategy in a Bayesian Structural VAR setup. We introduce a job reallocation shock, distinct from standard neutral technology shocks, matching efficiency shocks, labor supply shocks, or wage bargaining shocks. There is little evidence to suggest that the job reallocation shock played an especially large role, relative to other episodes, in driving the labor market through the first year of the pandemic. Aggregate demand was the primary driver of unemployment, hires and layoffs, with all other shocks having similar contributions. This is consistent with the view of the COVID-19 shock as reflecting low demand, lockdowns, supply bottlenecks, and low capacity utilization.

The results of the preceding analyses fail to provide evidence of a reallocation wave. It should be acknowledged that it is possible that highly stimulative policies may have prevented such a wave from materializing, for instance by reducing incentives of workers to look for jobs in growing sectors. At the same time, the reallocation argument would also affect job-to-job transitions. We have shown that, across sectors, there is little change in reallocation relative to pre-pandemic times. Reports by the California Policy Lab further showed that workers who lost their job in April 2020 had similar same-sector re-employment rates 12 months later across both hard-hit sectors and less affected ones. As such, we believe that, on the margin, UI generosity is unlikely to have affected our results. On the other hand, it is also conceivable that policy, through lockdowns and diversion of economic activity, combined with fear of the disease, induced itself some reallocation (Goolsbee & Syverson 2021); this would then imply a mostly temporary nature for such reallocation, which would vanish upon the removal of these policies and the eradication of the disease. It could possibly be too soon to tell whether COVID-19 induced a reallocation wave.

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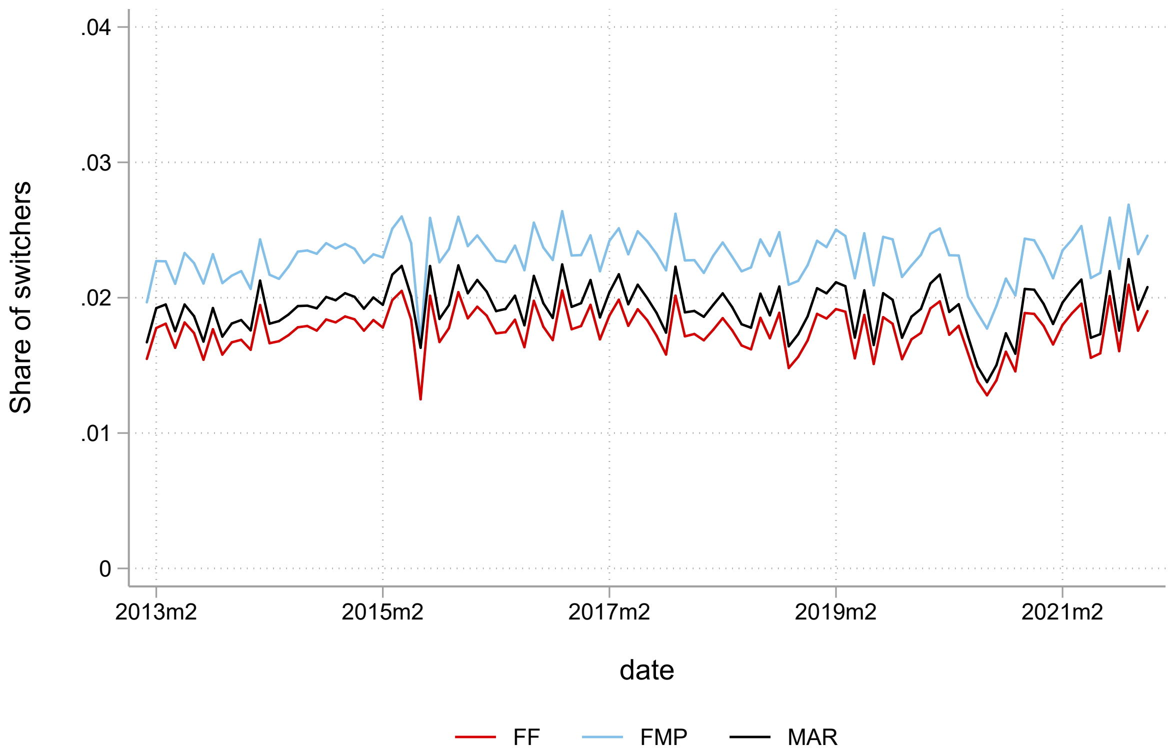
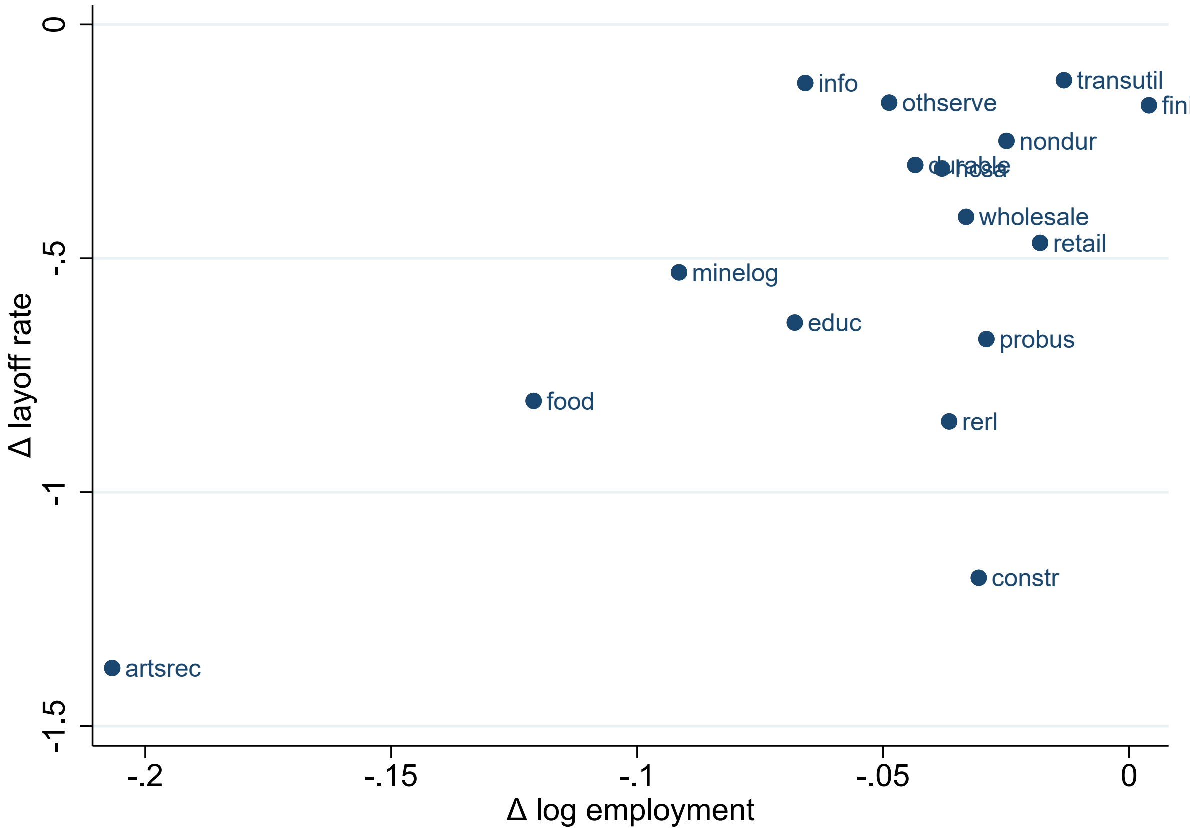
7 Additional Figures

Figure 9: Job-to-job transitions, seasonally adjusted



Notes: The chart shows the share of workers who switch employers (job-to-job transitions); FF uses the Fallick & Fleischman (2004) measure, FMP the Fujita et al. (2021) measure, and MAR a measure assuming missing observations are missing at random. The data for the RHS chart come from Fujita et al. (2021) and have been seasonally adjusted using the ratio-to-moving-average method.

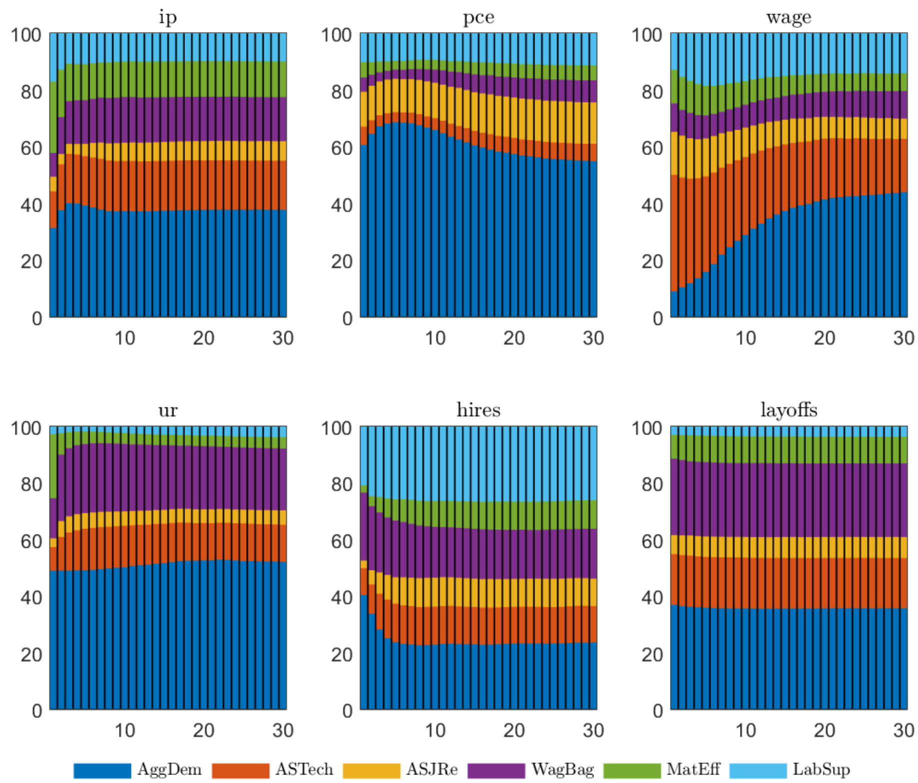
Figure 10: Change in layoff rate



Notes: The y-axis shows, for each sector, the change in the average layoff rate from the 2001-February 2020 period to the May 2021 - July2021 period. The x-axis shows the log change in employment from February 2020 to the average of the May 2021 - July2021 period. Source: JOLTS and CES.

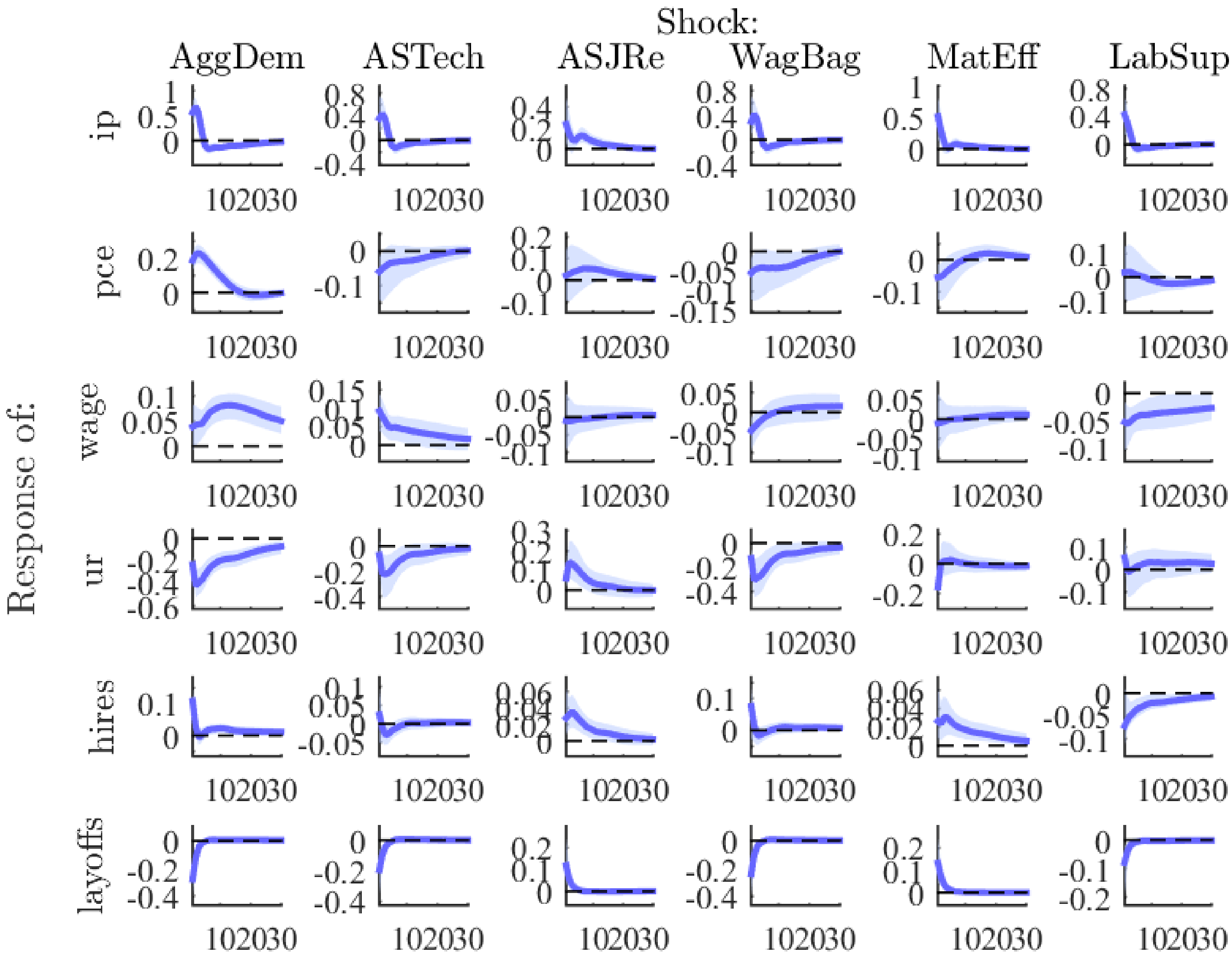
7.1 Baseline BVAR results

Figure 11: Forecast Error Variance Decomposition



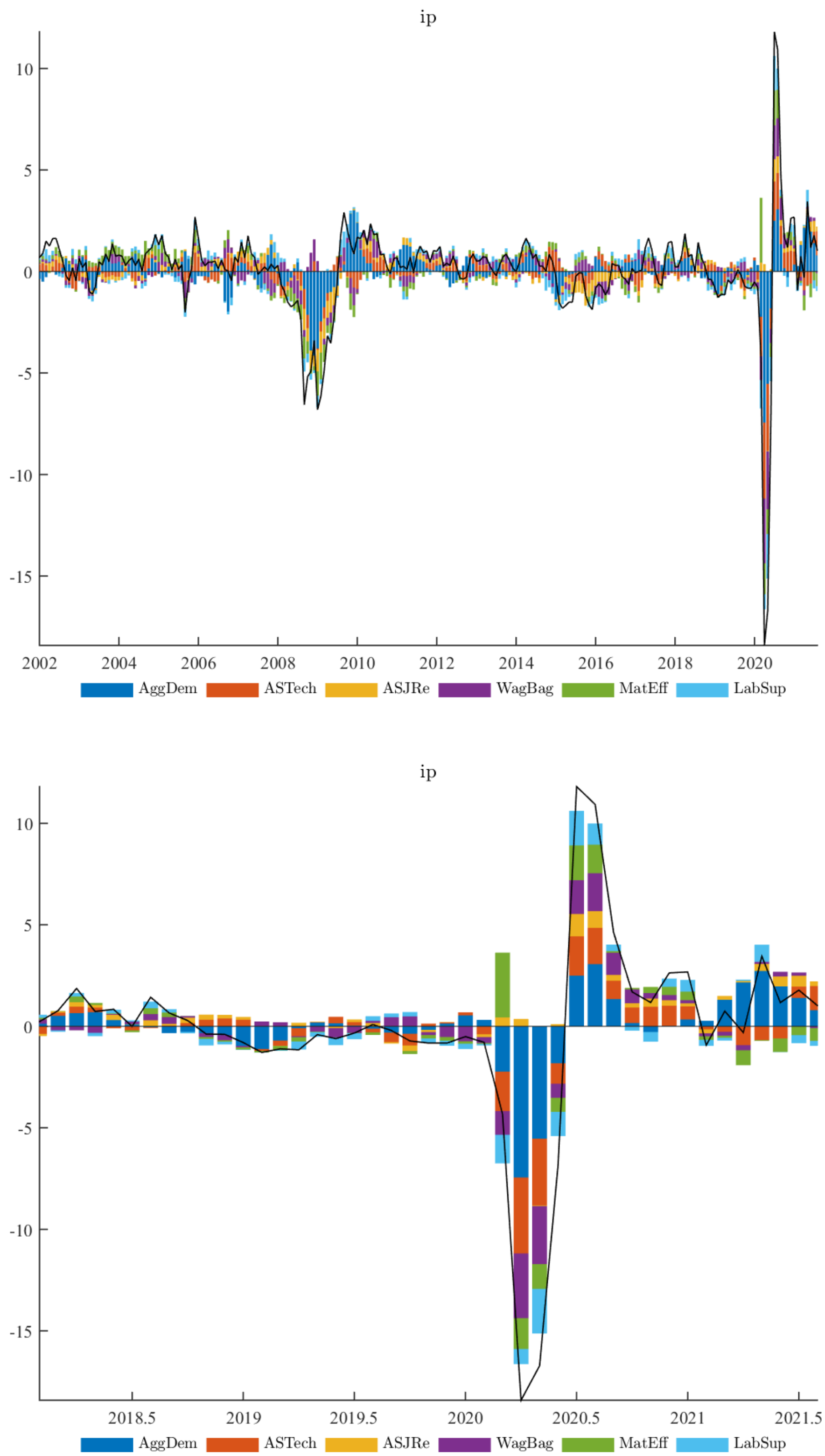
Notes: The table shows, for each of the variables in our VAR model, the share of the volatility explained by each shock. The vertical axis is in %, and the horizontal axis in months. *IP* refers to Industrial Production, *PCE* to personal consumption expenditure inflation, *Wages* to Atlanta Fed measure of nominal wages, *UR* to the unemployment rate. Similarly, *AggDem* refers to Aggregate Demand, *ASTech* to neutral technology, *ASJRe* to job reallocation, *WagBag* to wage bargaining, *MatEff* to matching efficiency, and *LabSup* to Labor Supply shock.

Figure 12: Impulse Responses



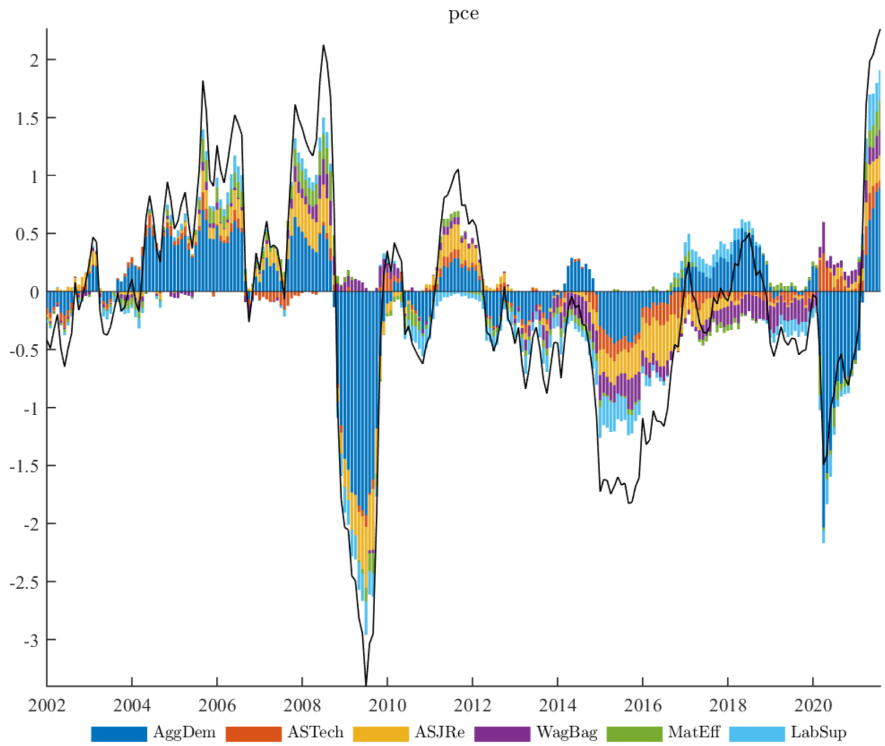
Notes: The figure shows impulse responses of all variables to all shocks in the SVAR model.

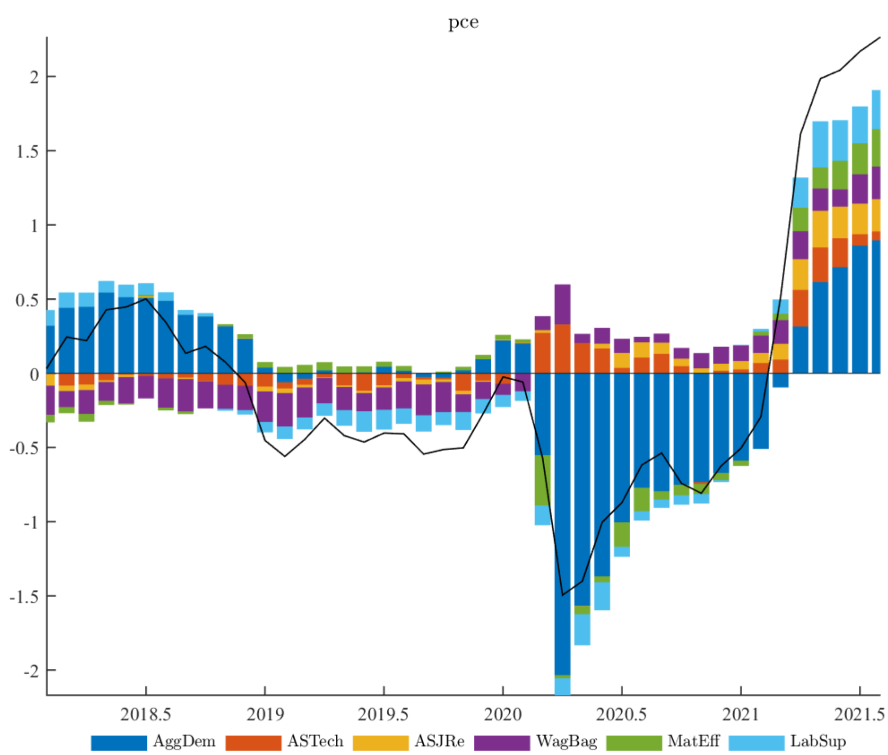
Figure 13: Industrial Production



Notes: The figures show the historical decomposition of shocks in the SVAR framework. The top figure shows the full sample (2001m1-2021m8), while the bottom one focuses on the sample since 2018.

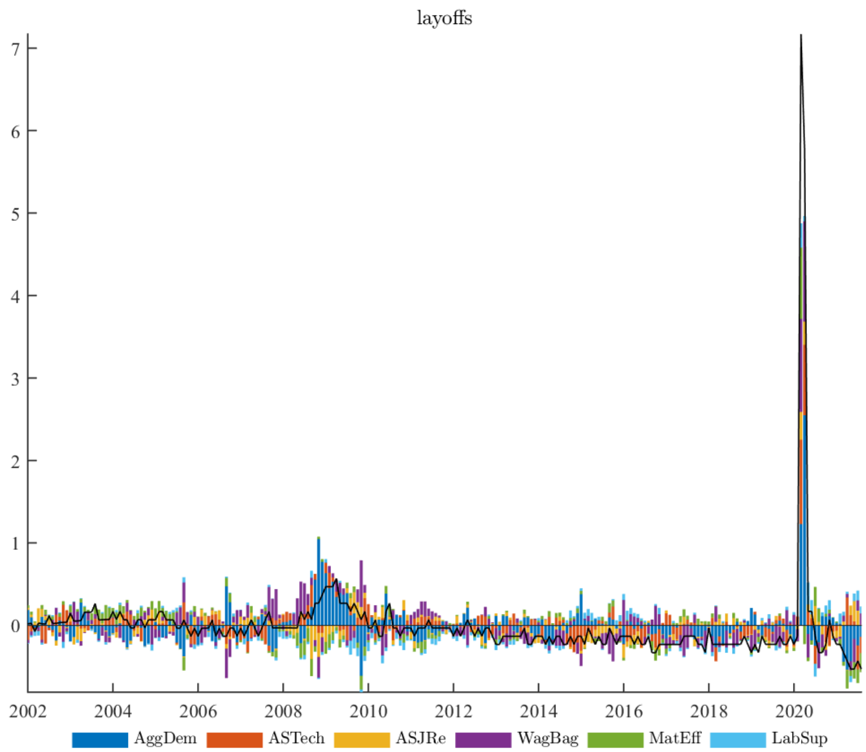
Figure 14: Price Inflation

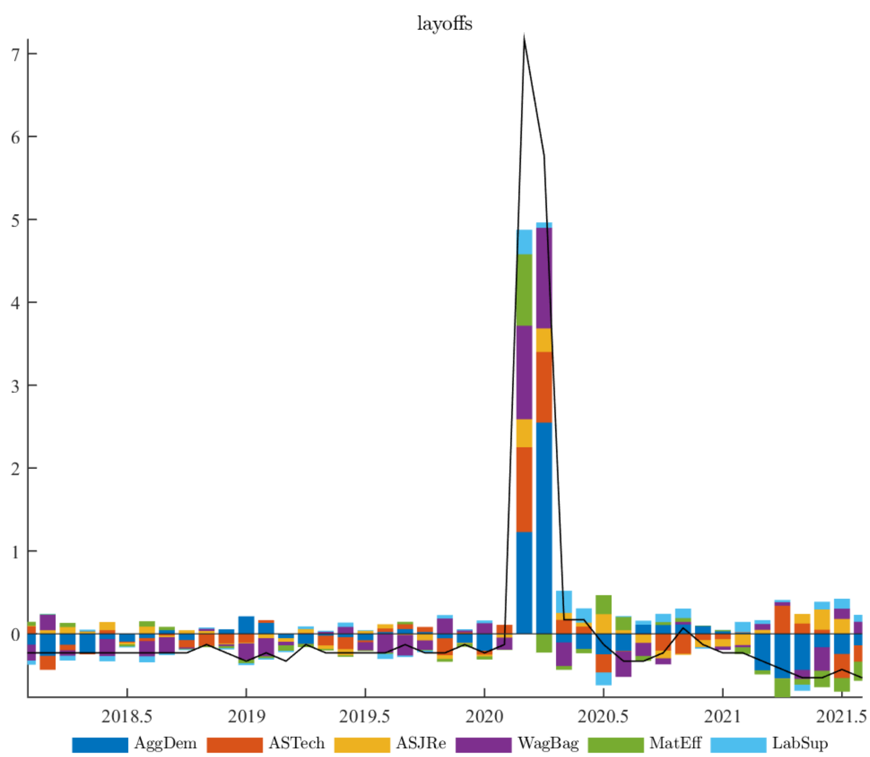




Notes: The figures show the historical decomposition of shocks in the SVAR framework. The top figure shows the full sample (2001m1-2021m8), while the bottom one focuses on the sample since 2018.

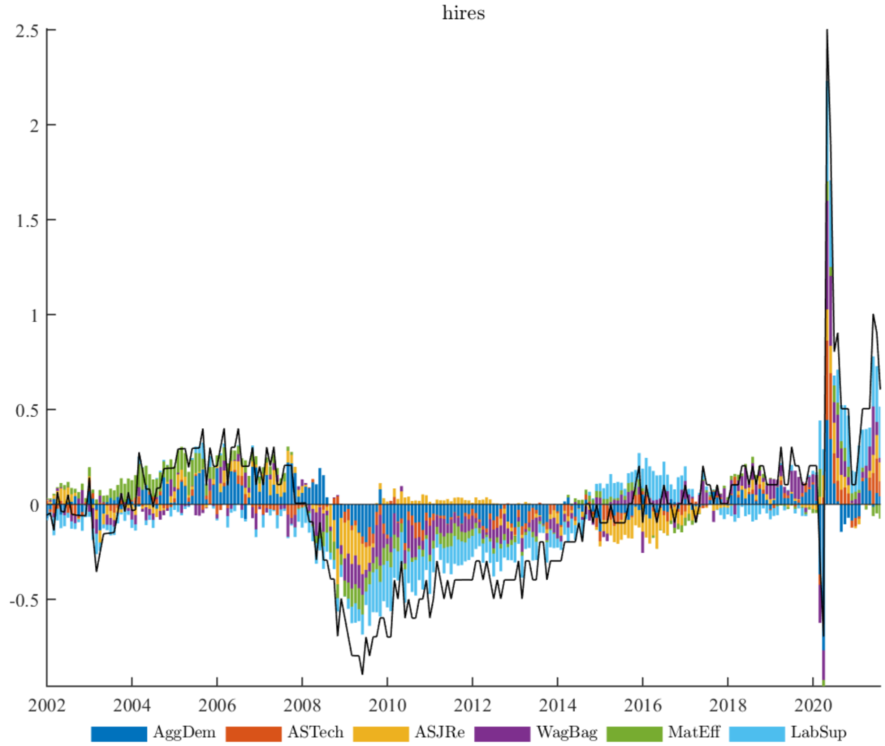
Figure 15: Layoffs

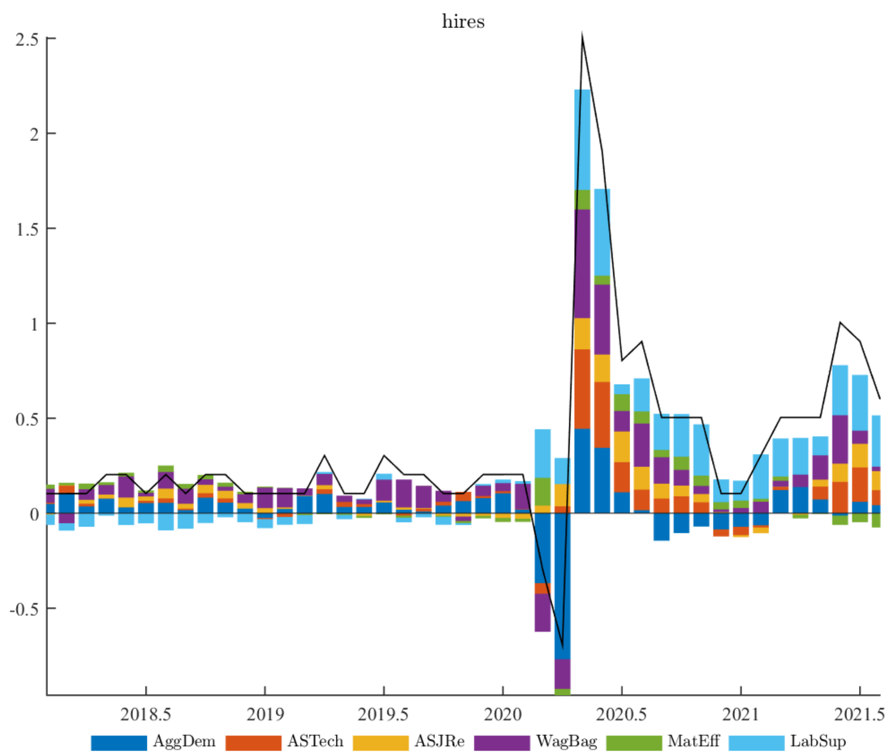




Notes: The figures show the historical decomposition of shocks in the SVAR framework. The top figure shows the full sample (2001m1-2021m8), while the bottom one focuses on the sample since 2018.

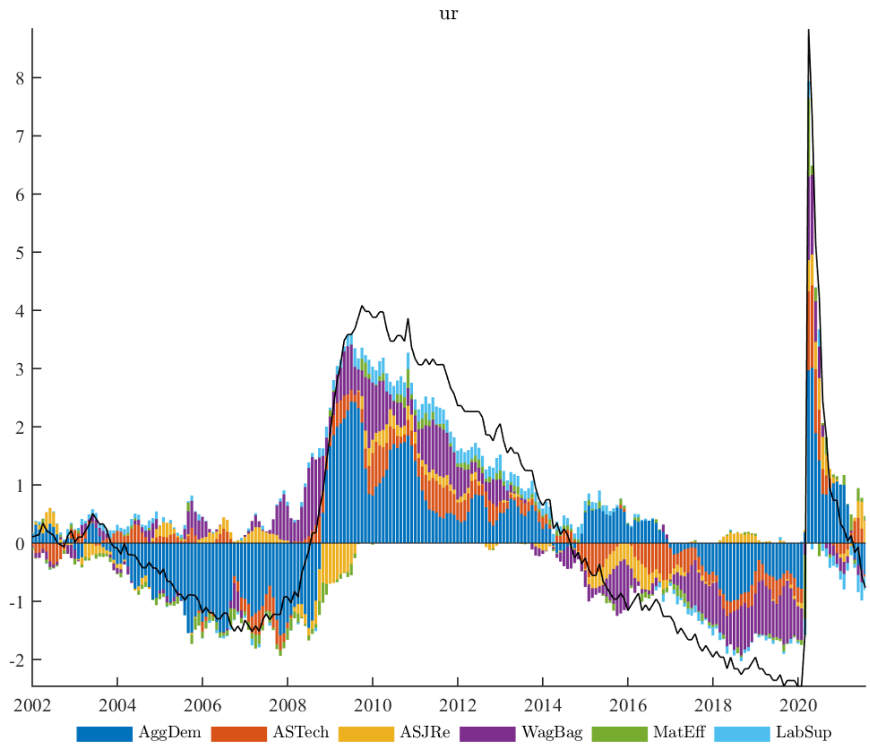
Figure 16: Hires

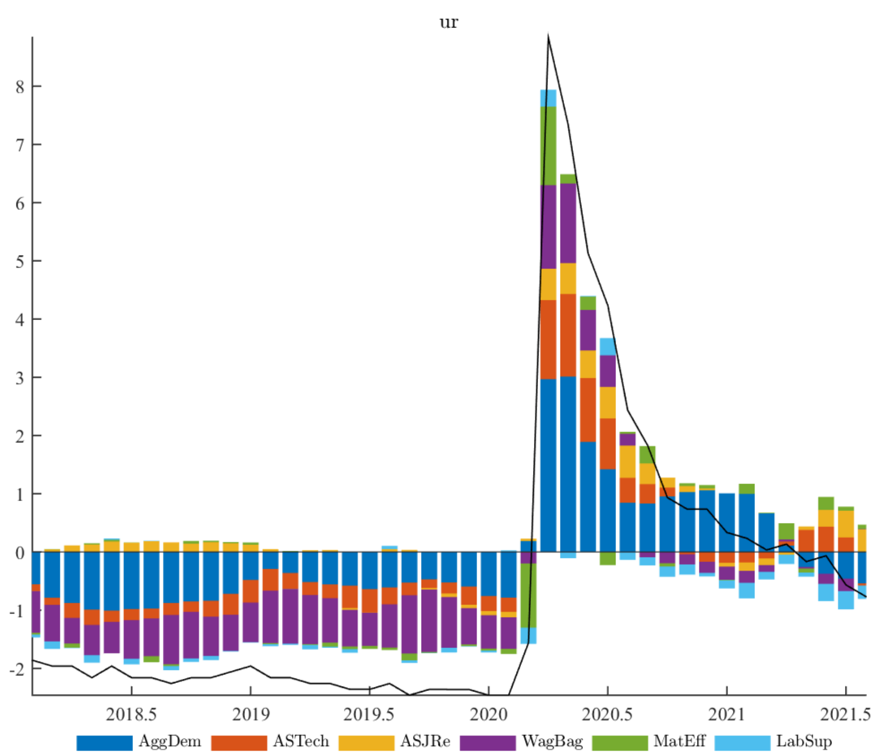




Notes: The figures show the historical decomposition of shocks in the SVAR framework. The top figure shows the full sample (2001m1-2021m8), while the bottom one focuses on the sample since 2018.

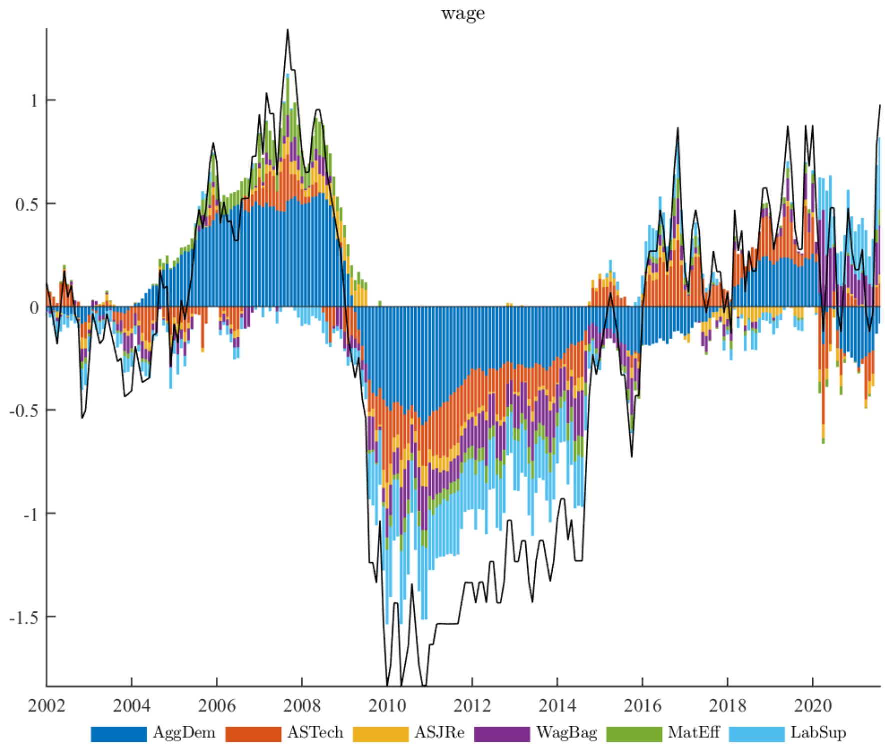
Figure 17: Unemployment Rate

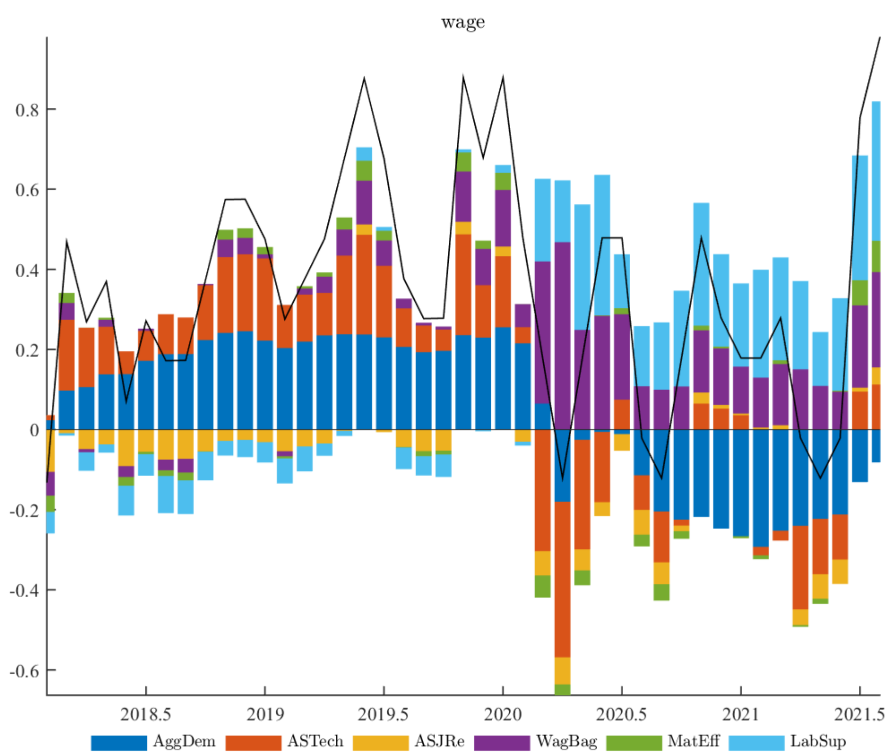




Notes: The figures show the historical decomposition of shocks in the SVAR framework. The top figure shows the full sample (2001m1-2021m8), while the bottom one focuses on the sample since 2018.

Figure 18: Wages

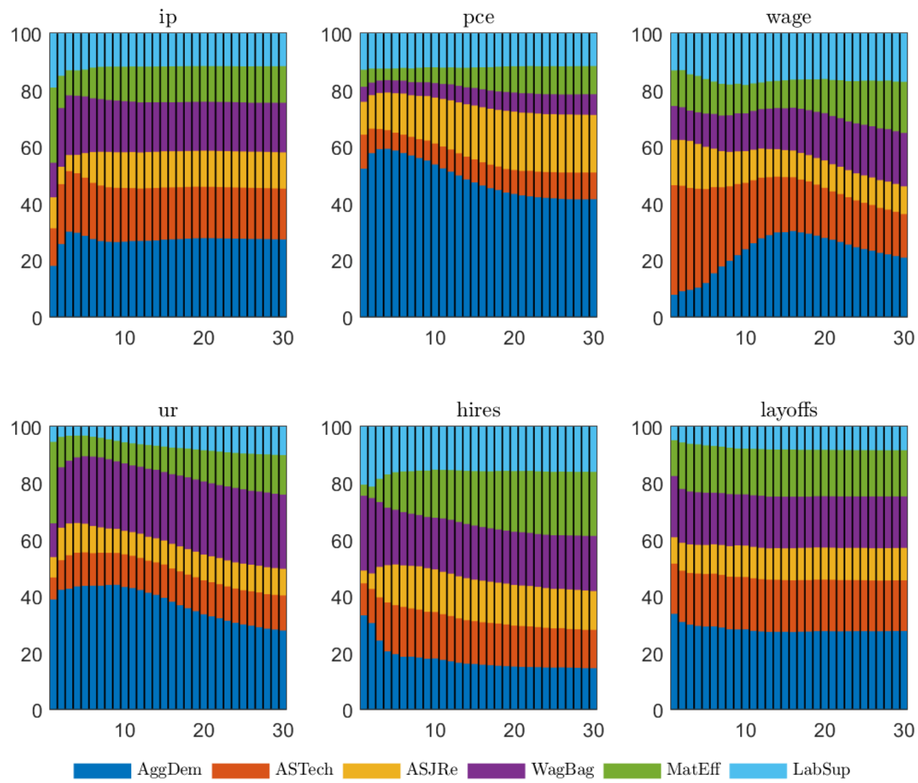




Notes: The figures show the historical decomposition of shocks in the SVAR framework. The top figure shows the full sample (2001m1-2021m8), while the bottom one focuses on the sample since 2018.

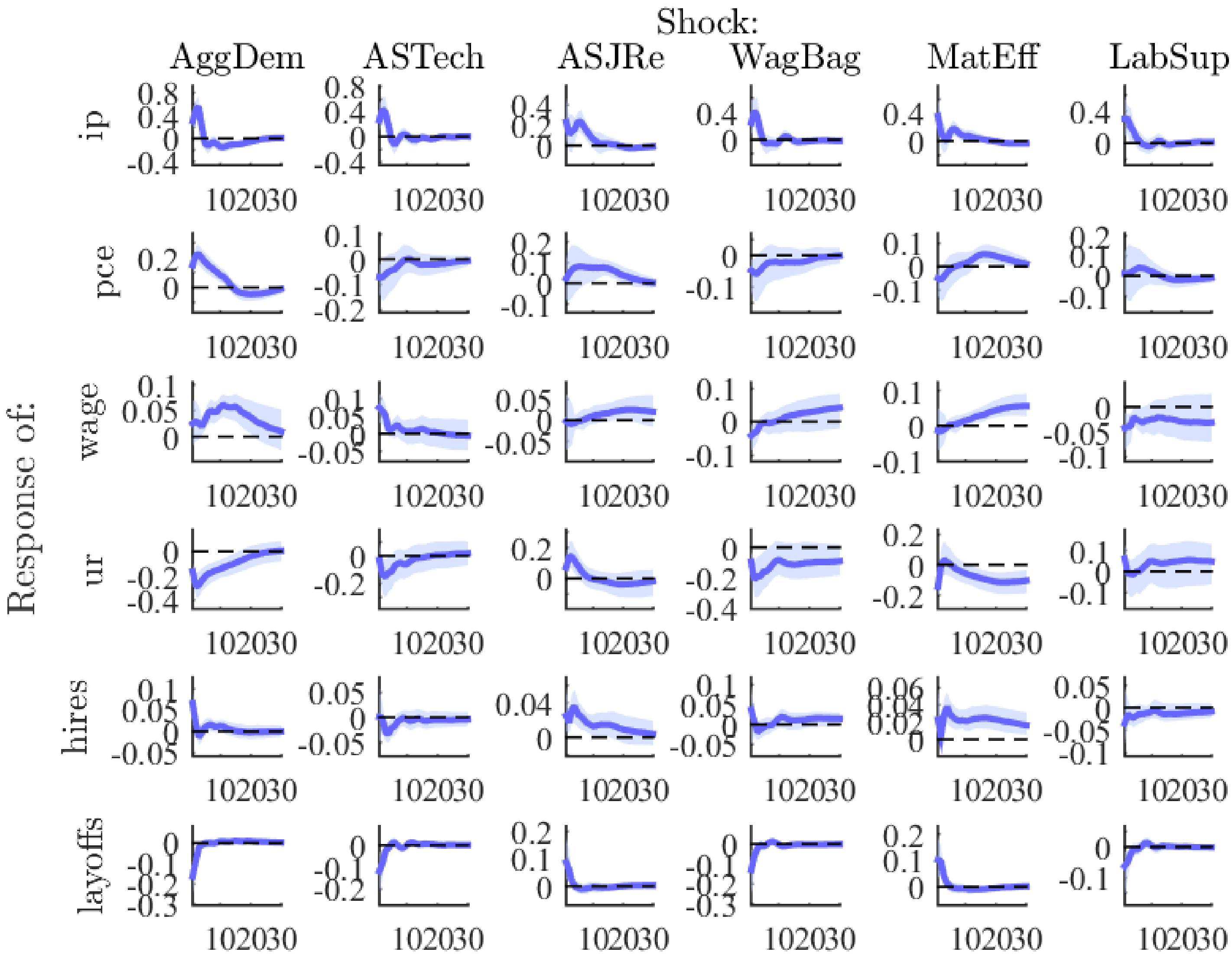
7.2 BVAR with Pandemic Priors

Figure 19: Forecast Error Variance Decomposition



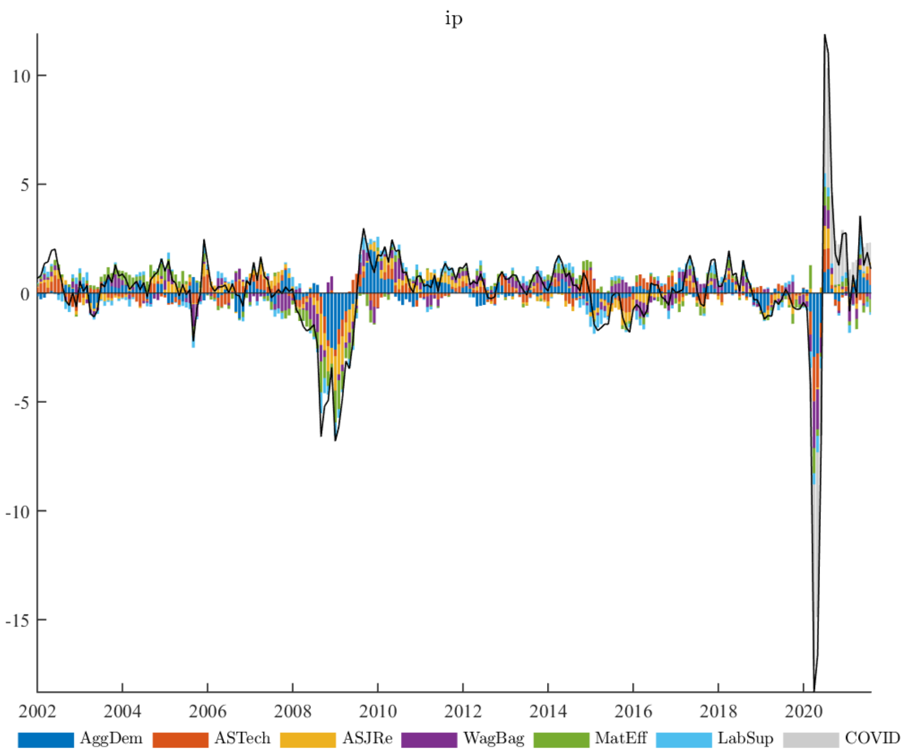
Notes: The table shows, for each of the variables in our VAR model, the share of the volatility explained by each shock. The vertical axis is in %, and the horizontal axis in months. *IP* refers to Industrial Production, *PCE* to personal consumption expenditure inflation, *Wages* to Atlanta Fed measure of nominal wages, *UR* to the unemployment rate. Similarly, *AggDem* refers to Aggregate Demand, *ASTech* to neutral technology, *ASJRe* to job reallocation, *WagBag* to wage bargaining, *MatEff* to matching efficiency, and *LabSup* to Labor Supply shock.

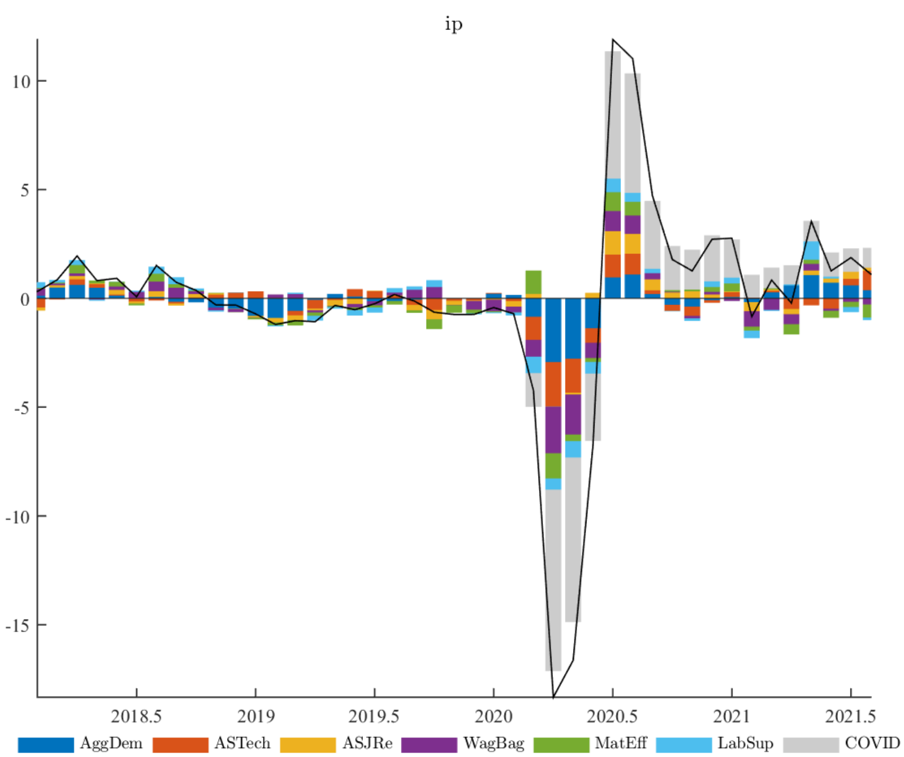
Figure 20: Impulse Responses



Notes: The figure shows impulse responses of all variables to all shocks in the SVAR model.

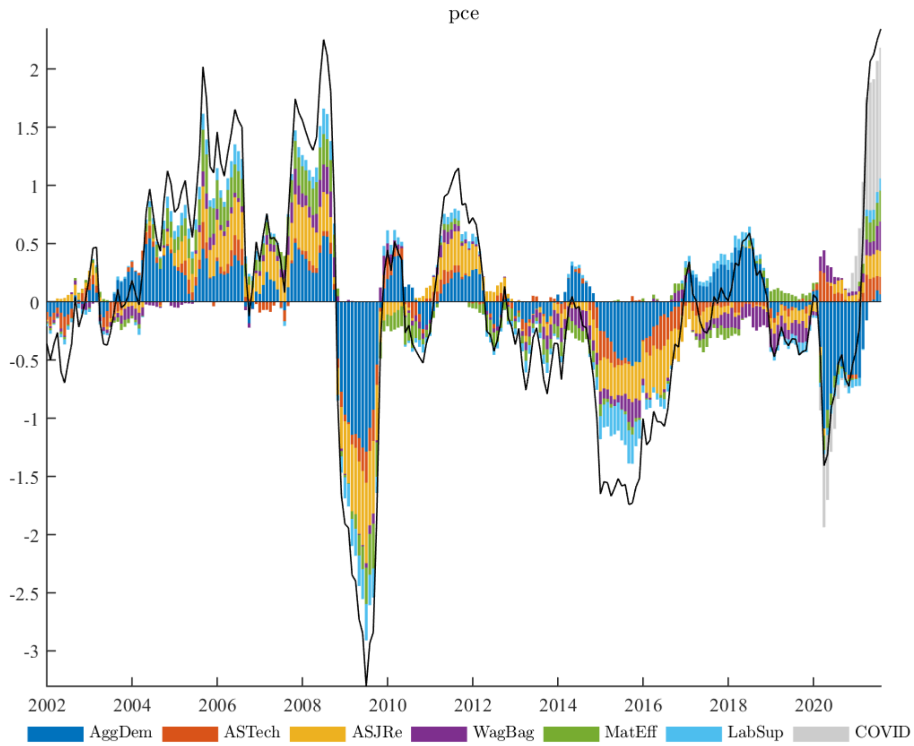
Figure 21: Industrial Production

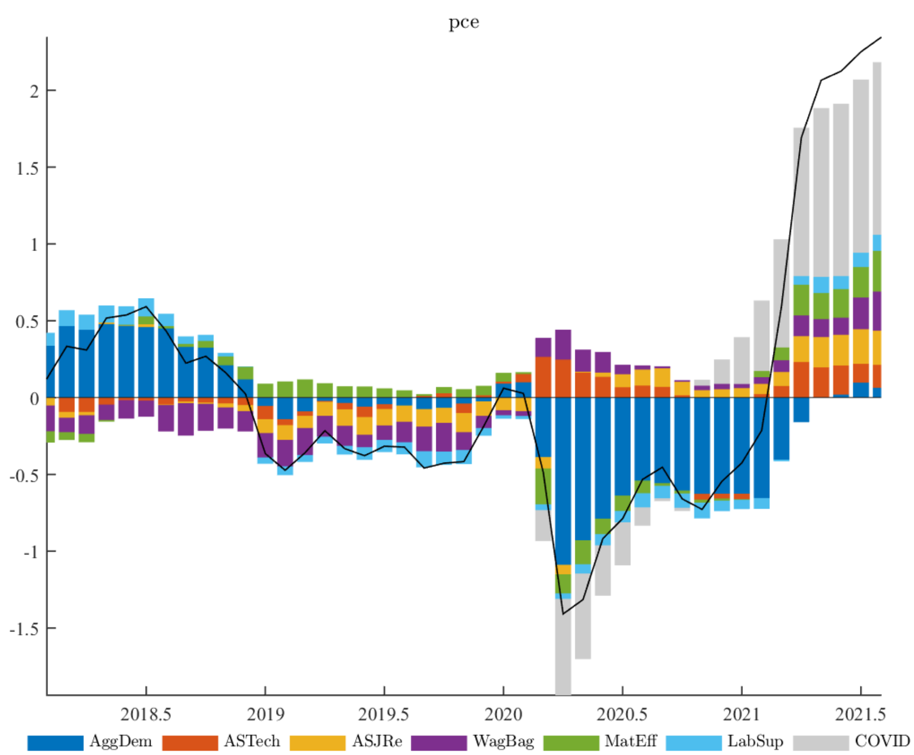




Notes: The figures show the historical decomposition of shocks in the SVAR framework, using the Pandemic Priors approach of Cascaldi-Garcia (2022). The top figure shows the full sample (2001m1-2021m8), while the bottom one focuses on the sample since 2018.

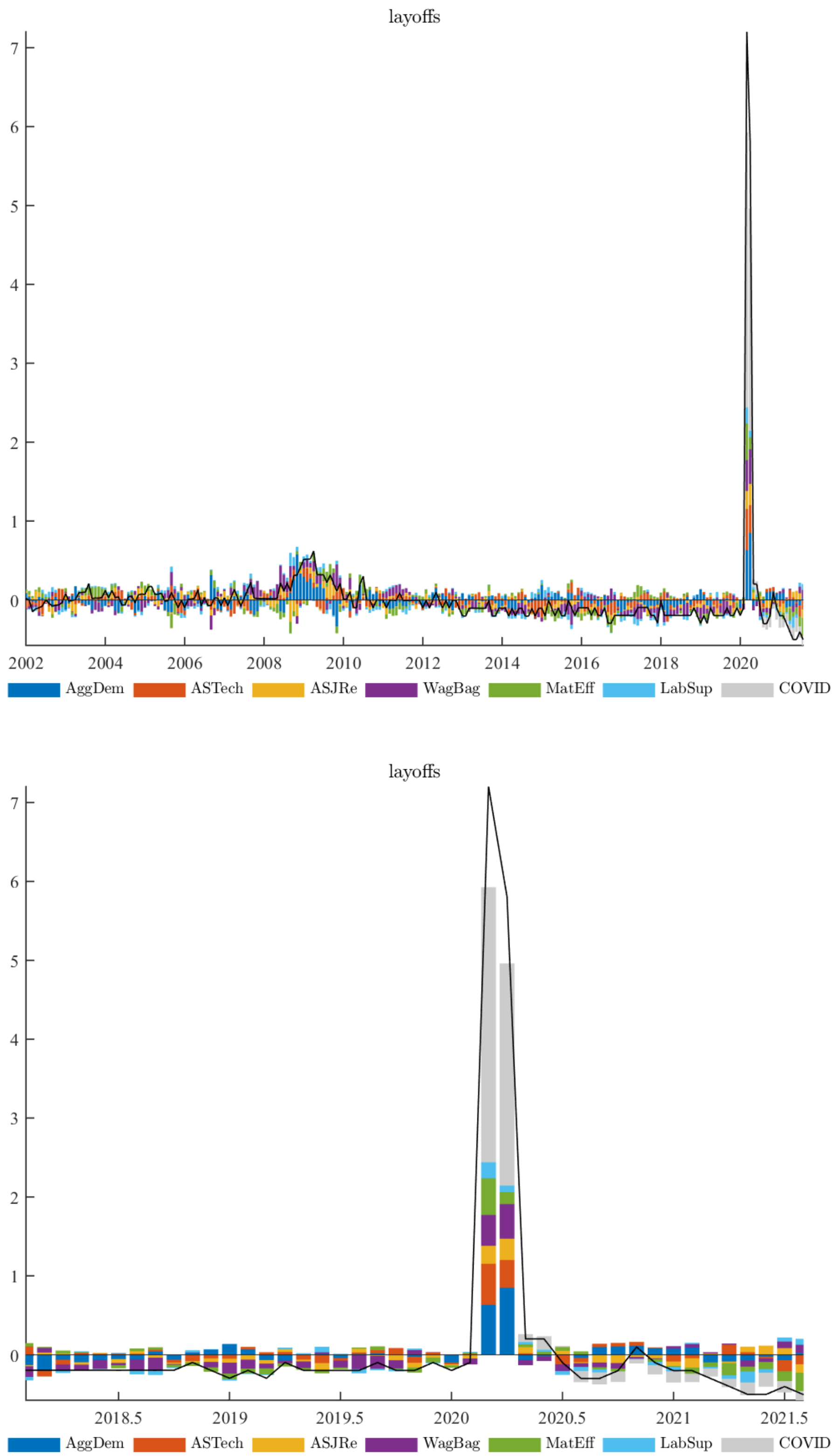
Figure 22: Inflation





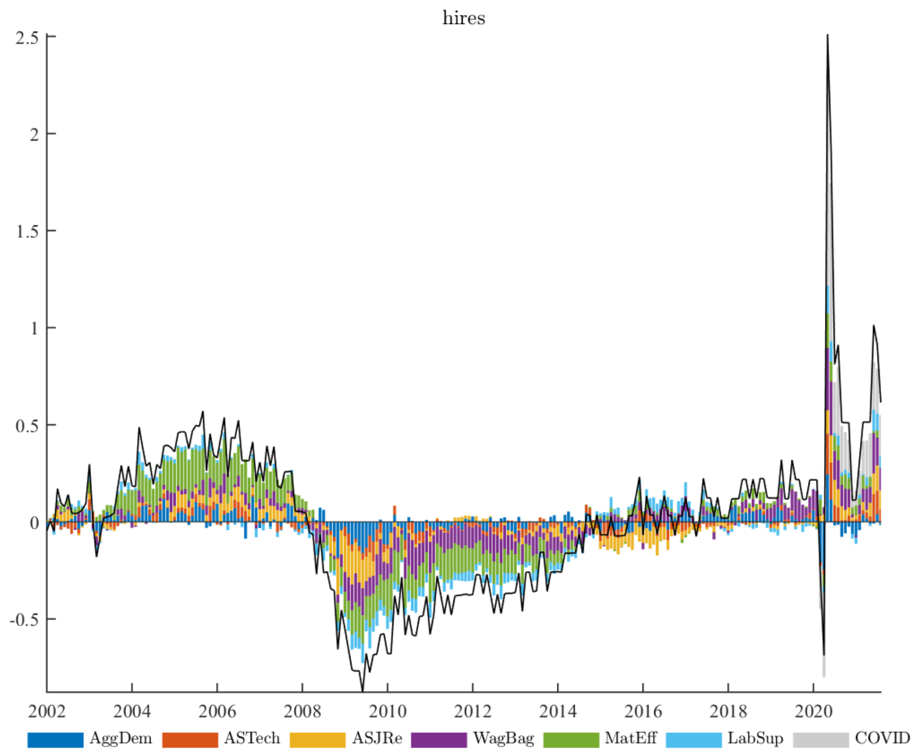
Notes: The figures show the historical decomposition of shocks in the SVAR framework, using the Pandemic Priors approach of Cascaldi-Garcia (2022). The top figure shows the full sample (2001m1-2021m8), while the bottom one focuses on the sample since 2018.

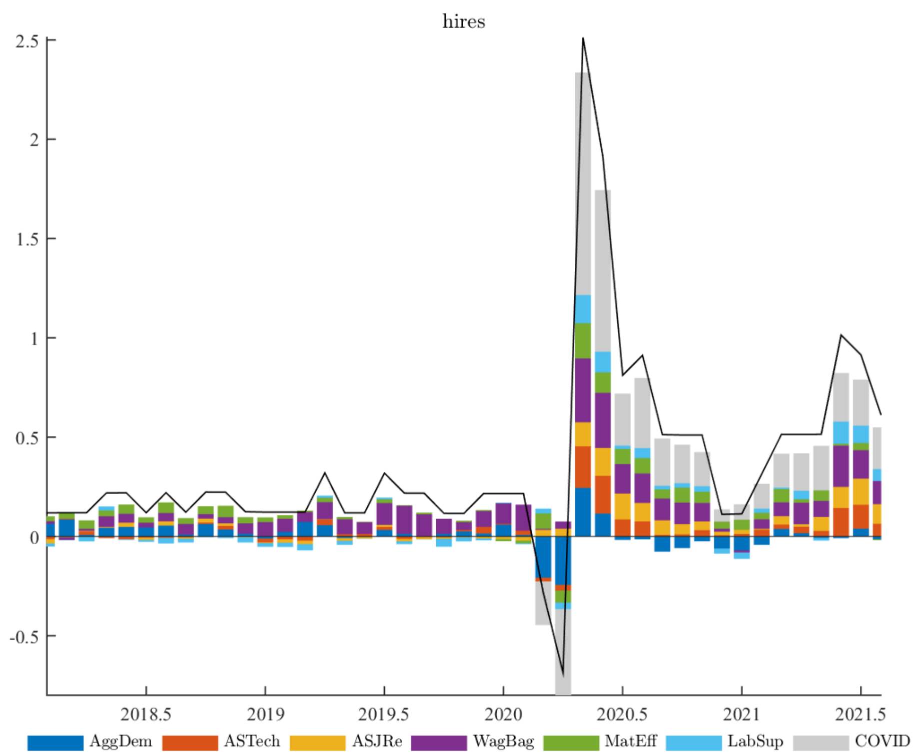
Figure 23: Layoffs



Notes: The figures show the historical decomposition of shocks in the SVAR framework, using the Pandemic Priors approach of Cascaldi-Garcia (2022). The top figure shows the full sample (2001m1-2021m8), while the bottom one focuses on the sample since 2018.

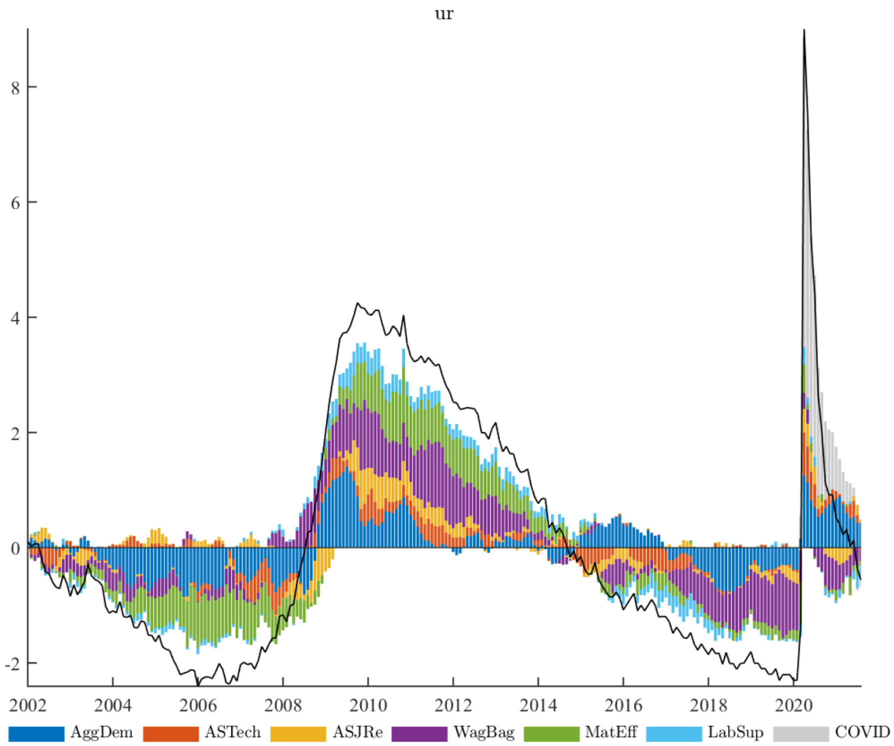
Figure 24: Hires

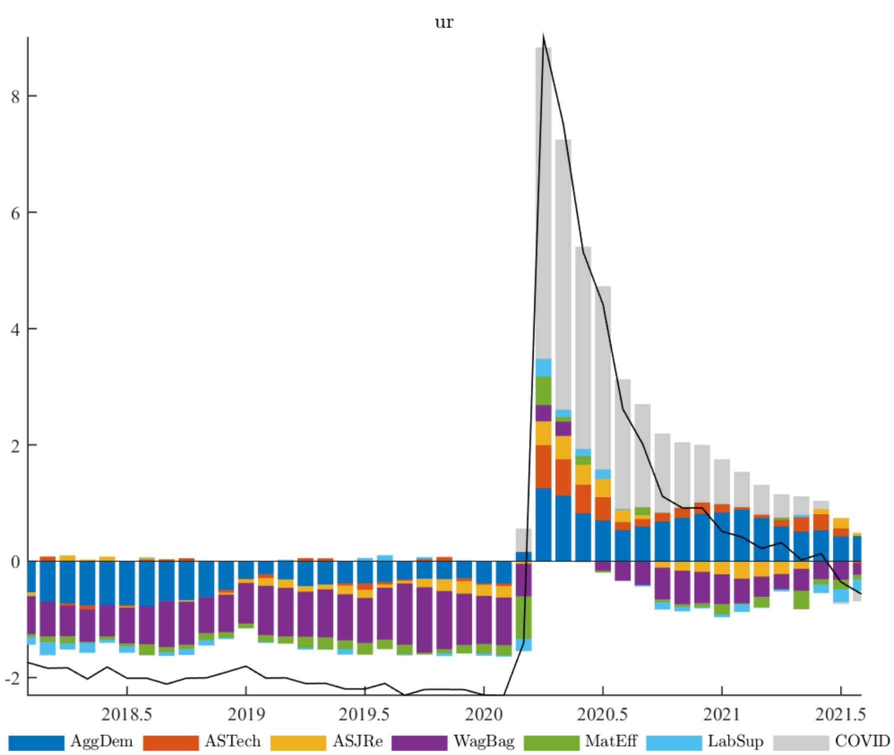




Notes: The figures show the historical decomposition of shocks in the SVAR framework, using the Pandemic Priors approach of Cascaldi-Garcia (2022). The top figure shows the full sample (2001m1-2021m8), while the bottom one focuses on the sample since 2018.

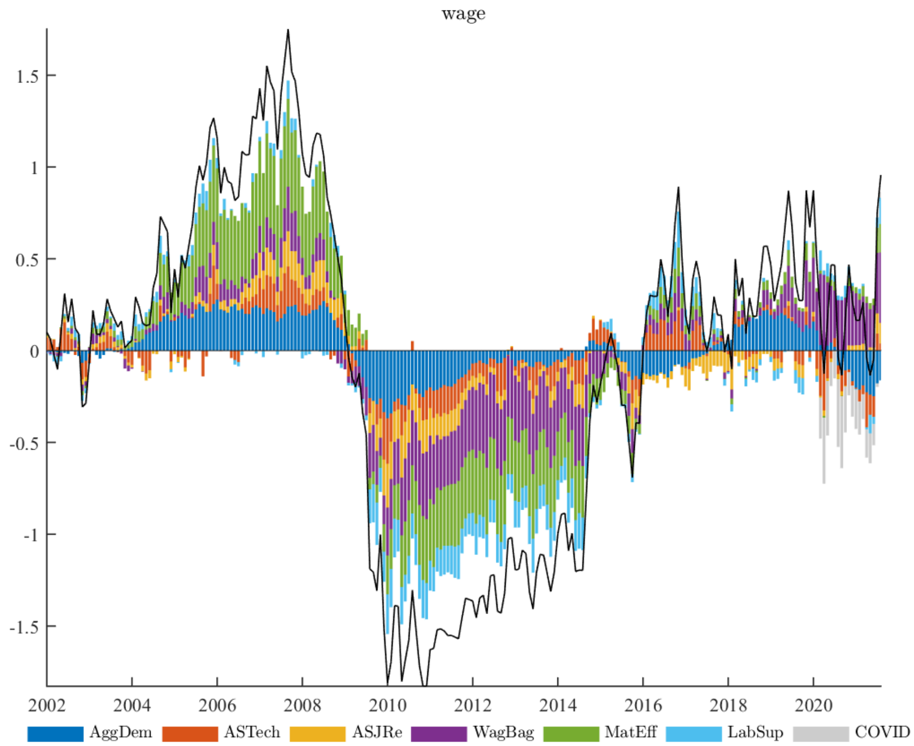
Figure 25: Unemployment Rate

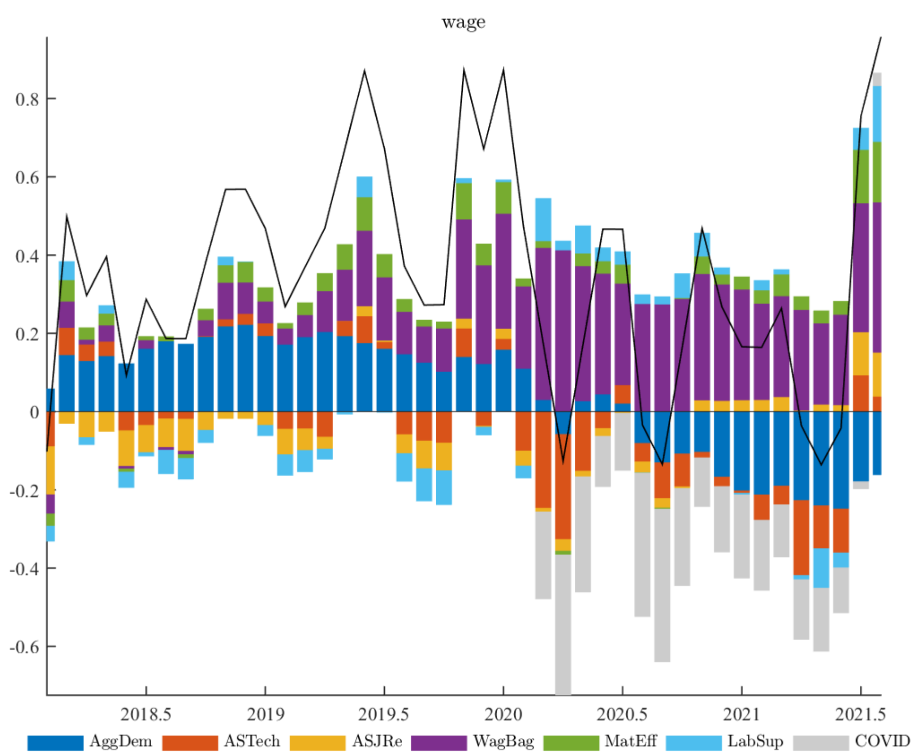




Notes: The figures show the historical decomposition of shocks in the SVAR framework, using the Pandemic Priors approach of Cascaldi-Garcia (2022). The top figure shows the full sample (2001m1-2021m8), while the bottom one focuses on the sample since 2018.

Figure 26: Wages





Notes: The figures show the historical decomposition of shocks in the SVAR framework, using the Pandemic Priors approach of Cascaldi-Garcia (2022). The top figure shows the full sample (2001m1-2021m8), while the bottom one focuses on the sample since 2018.