Appendix to 'Fiscal Policy and Occupational Employment Dynamics'

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Contents

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A Data appendix

A.1 Occupational labor market data

The CPS is a representative monthly household survey conducted by the U.S. Bureau of Labor Statistics, covering a number of demographic and labor-market related questions. The Merged Outgoing Rotation Group (MORG) is a subset of the full CPS sample (more than 25,000 individuals per month) and can be downloaded from the National Bureau of Economic Research. CEPR has prepared several consistent datasets from the CPS available for download. We use these data and checked that aggregating the monthly CPS micro data to quarterly, seasonally adjusted time series yields virtually identical time series as published by the BLS.

Changes in the way the Census defines industries and occupations affect the comparability of the employment series over time. To construct consistent occupational employment data over time, we follow the procedure outlined in Shim and Yang (2016) and use conversion factors provided by the U.S. Census Bureau. Analogously, we use the Census-provided conversion factors for industries to construct consistent employment series by industries. The major occupation and industry groups follow the 2010 Census classification.

We include individuals aged 16 and over and use the CPS Earnings Weight when collapsing the micro data. The CPS Labor Force Status variable is used to classify individuals as employed. To measure hours worked, we use the CPS information on hours worked last week at all jobs. The earnings variable is taken from the CEPR extracts and is defined as usual weekly earnings for hourly and non-hourly workers, including overtime compensation. Nominal variables are converted to \$2015 using the U.S. Consumer Price Index.

Note that the conversion factors have been determined for constructing consistent employment series by occupation or industry, respectively. To construct consistent time series for other labor-market outcomes than employment, we use the original conversion factors but adjust the resulting time series using dummies when detrending the (log) data. The dummies shift the series by a constant factor, analogous to the procedure used by Foote and Ryan (2016), and hence assumes that the constant difference between the employment-specific conversion factor matrices and the respective matrix for other labor-market outcomes affects mostly the level of the resulting series. For linear trends, we determine the cyclical component of $\ln x$ in occupation o as the residual to the regression $\ln \widehat{x}_{o,t} = const_{x,o} + \beta_{x,o} \cdot t + \gamma_{x,o} \cdot 1_{t<2003} + \varepsilon_{x,o,t}$, where $1_{t<2003}$ is an indicator variable for the time before 2003, the year where the classification of major occupations has changed to the current classification. We proceed analogously to construct the time series of employment by occupation *and* industry.

A.2 Aggregate data

Table A.1 summarizes the data sources for the aggregate data and Table A.2 shows how we construct the aggregate variables that enter the VARs.

Table A1: Data sources

Series Title	Series ID	Source
Government Consumption Expenditures	A955RC1Q027SBEA	FRED
Gross Government Investment	A782RC1Q027SBEA	FRED
Gross Domestic Product	GDP	FRED
Gross Domestic Product: Implicit Price Deflator	GDPDEF	FRED
Civilian Noninstitutional Population	CNP16OV	FRED
Effective Federal Funds Rate	FEDFUNDS	FRED
Current Tax Receipts	W054RC1Q027SBEA	FRED
Public Debt as Percent of GDP	GFDEGDQ188S	FRED
Mean Forecast for Real Federal Government Consumption Expenditures and Gross Investment	Mean_RFEDGOV_Level	SPF
Mean Forecast for Real State and Local Government Consumption Expenditures and Gross Investment	Mean_RSLGOV_Level	SPF
Government Consumption Expenditures: Gross Output of General Government: Value Added: Compensation of General Government Employees	A194RC1Q027SBEA	FRED
Capacity Utilization: Total Industry	TCU	FRED

Notes: FRED: Federal Reserve Bank of St. Louis Economic Database, SPF: Survey of Professional Forecasters.

Table A2: Definition of variables

Variable	**Definition**	**Description**
Output	$\log \frac{GDP}{GDPDEF \cdot CNP16OV}$	real GDP per capita
Government Spending	$\log \frac{(A955...)+(A782...)}{GDPDEF \cdot CNP16OV}$	real government spending per capita
Government Consumption	$\log \frac{(A955...)}{GDPDEF \cdot CNP16OV}$	real government consumption per capita
Government Investment	$\log \frac{(A782...)}{GDPDEF \cdot CNP16OV}$	real government investment per capita
Tax Receipts	$\log \frac{W054RC1Q027SBEA}{GDPDEF \cdot CNP16OV}$	real government tax receipts per capita
Debt-to-GDP Ratio	$GFDEGDQ188S$	public debt as percent of GDP
Real Interest Rate	$\frac{FEDFUNDS}{100} - \left(\frac{GDPDEF(+1)}{GDPDEF}\right)^4 - 1$	annualized real interest rate
Government Spending Forecast	$\left(\frac{(RFEDGOV+RLSGOV)(+1)}{(RFEDGOV+RLSGOV)}\right)^4 - 1$	forecast made at time t for growth rate of government spending at time $t+1$, annualized
Government Wage-Bill Expenditures	$\log \frac{A194RC1Q027SBEA}{GDPDEF \cdot CNP16OV}$	real government wage bill per capita
Government Non-Wage Expenditures	$\log \frac{(A955...)+(A782...)-(A194...)}{GDPDEF \cdot CNP16OV}$	real government non-wage bill expenditure per capita
Labor market variables	see Appendix A.1	–

Notes: (+1) indicates a one-quarter lead.

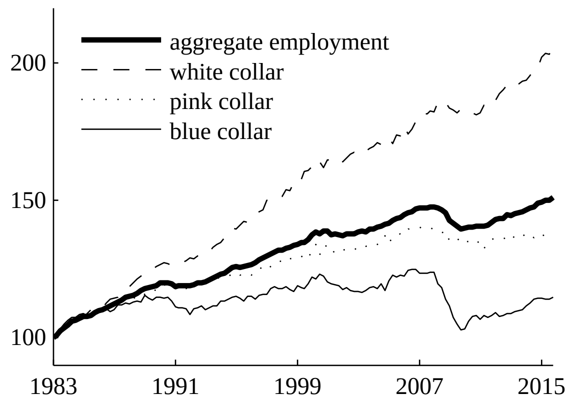
B Descriptive developments in occupational employment

Figure A1 shows seasonally adjusted, quarterly time series for aggregate employment and employment in the three broad occupation groups white-collar, blue-collar, and pink-collar. For comparability, we have normalized the first value (1983Q1) to 100.

The figure shows that the different occupation groups have different employment trends. Aggregate employment grows at an average rate of 0.27 percent per quarter or 1.1 percent per year, roughly the rate of population growth in our sample. Employment growth amounts to about 0.5 percent per quarter (2 percent per year) for white-collar occupations, 0.22 percent per quarter (0.88 percent per year) for pink-collar occupations, and 0.1 percent per quarter (0.4 percent per year) for blue-collar occupations. As a consequence, the share of blue-collar employment in total employment falls, from 27.7 percent in 1983Q1 to 21.0 percent in 2015Q4.

The figure also illustrates that blue-collar employment is more volatile than employment in other occupation groups. Clearly, blue-collar employment exhibits the strongest fall during the Great Recession. It also shows the most pronounced drops during the other two recessions in our sample, i.e., in the early 1990s and the early 2000s. The main text provides some unconditional moments of cyclical occupational employment, i.e., percentage deviations from log-linear trends.

Figure A1: Descriptive development in aggregate, white-collar, pink-collar, and blue-collar employment (1983Q1 = 100).



Notes: Seasonally adjusted time series of aggregate, white-collar, pink-collar, and blue-collar employment. Consistent occupational employment series achieved through conversion factors provided by the BLS. For each series, the value in 1983.I is normalized to 100. The non-normalized values in 1983Q1 are about 99.2 million for aggregate employment, 28.5 million for white-collar employment, 43.3 million for pink-collar employment, and 27.4 million for blue-collar employment. Pink collar: service occupations; sales and related occupations; office and administrative support occupations. Blue collar: construction and extraction occupations; installation, maintenance, and repair occupations; production occupations; transportation and material moving occupations. White collar: management, business, and financial occupations; professional and related occupations.

C Empirical results

In this appendix, we first present the full set of responses of macroeconomic aggregates included in the VAR to government spending expansions. Second, we present additional results on occupational employment dynamics in response to fiscal policy. Third, we present detailed results of the additional specifications discussed in Section 3 of the main text (alternative VAR specifications, alternative identification of fiscal shocks, and disentangling government investment and government consumption). Fourth, we discuss employment dynamics in specific sectors and industry groups. Finally, we discuss how we construct a time series of occupational employment which is unrelated to industry dynamics and present estimation results for the constructed series.

C.1 Detailed estimation results

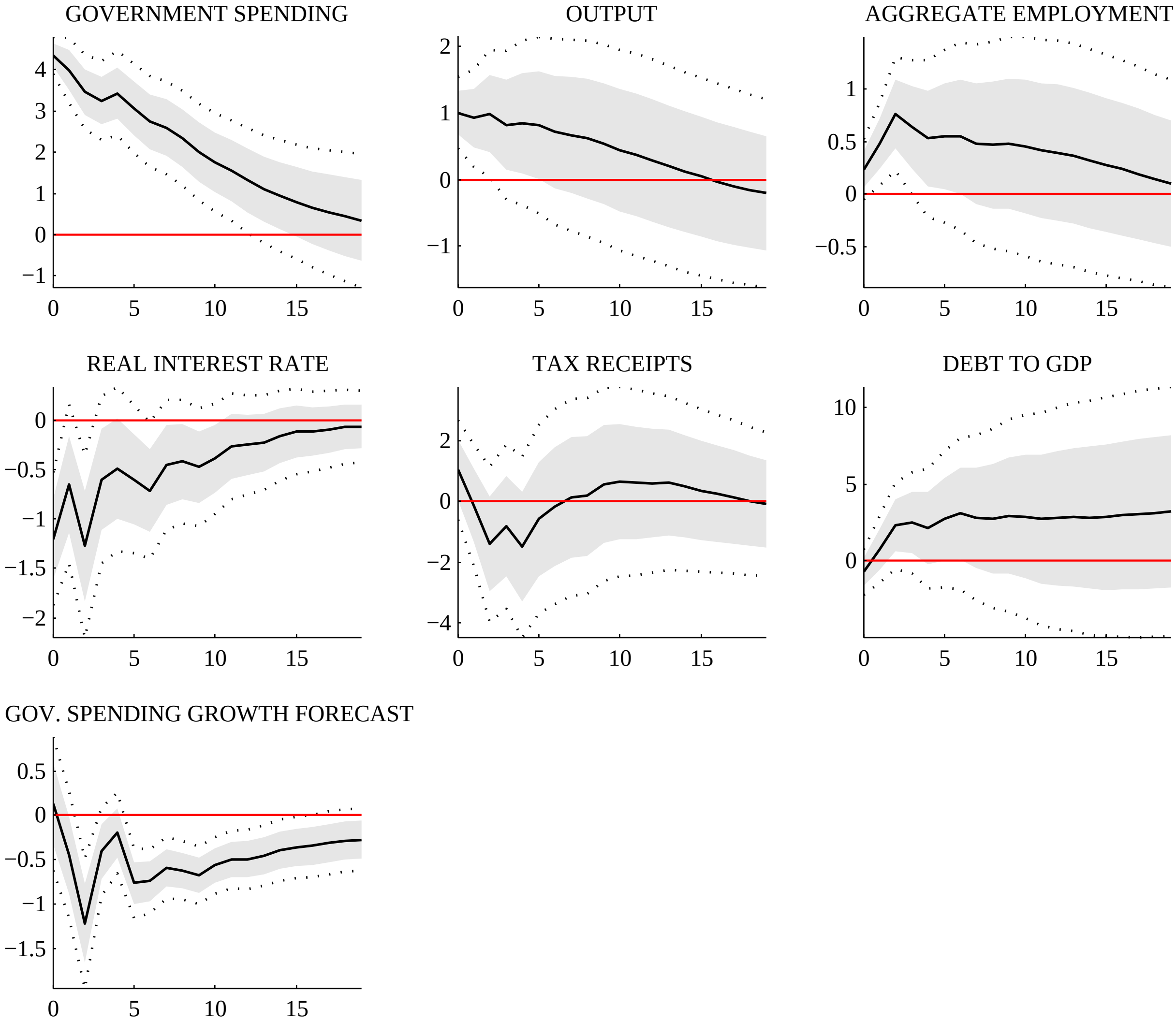
Figure A2 displays the estimated responses of macroeconomic aggregates to government spending shocks. The horizontal axes show quarters after the shock and the responses are expressed in percentage terms. The shock is normalized such that output changes by 1% on impact. We observe a persistent rise in government spending, a significant increase in output, and a significant and hump-shaped increase in aggregate employment. The debt-to-GDP ratio increases, indicating that the fiscal stimulus is partly debt-financed. Monetary policy seems to accommodate fiscal policy as the real interest rate falls. This finding is consistent with evidence provided by, e.g., Mountford and Uhlig (2009) and Ramey (2016).

C.2 Additional results on occupational employment dynamics

Figure A3 shows the responses of employment in the major subcategories of pink-collar occupations, i.e., service occupations, sales occupations, and office occupations, to the government spending shock. Employment rises in all subcategories of pink-collar occupations. The most significant and most persistent increase is observed for service occupations.

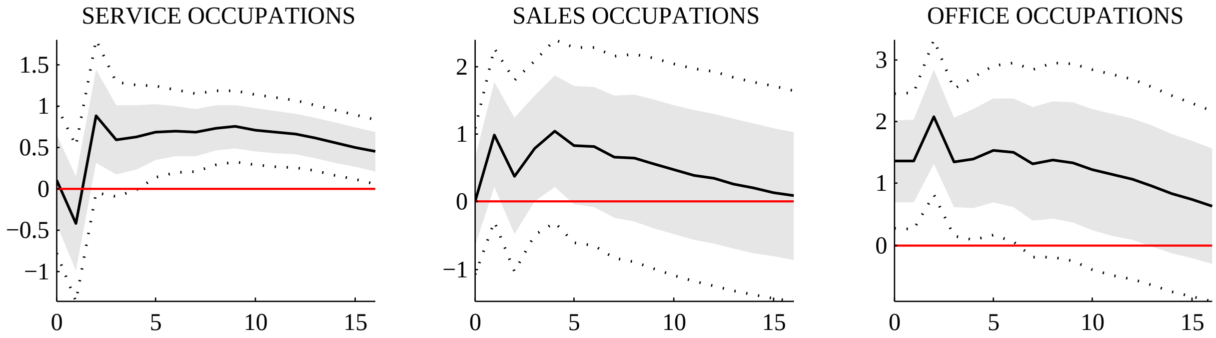
Figure A4 repeats the analysis for the four subcategories of blue-collar occupations. Strikingly, and in sharp contrast to the subcategories of pink-collar occupations, we do not find a significant surge in employment for any blue-collar major occupation.

Figure A2: The effects of government spending shocks on macroeconomic aggregates.



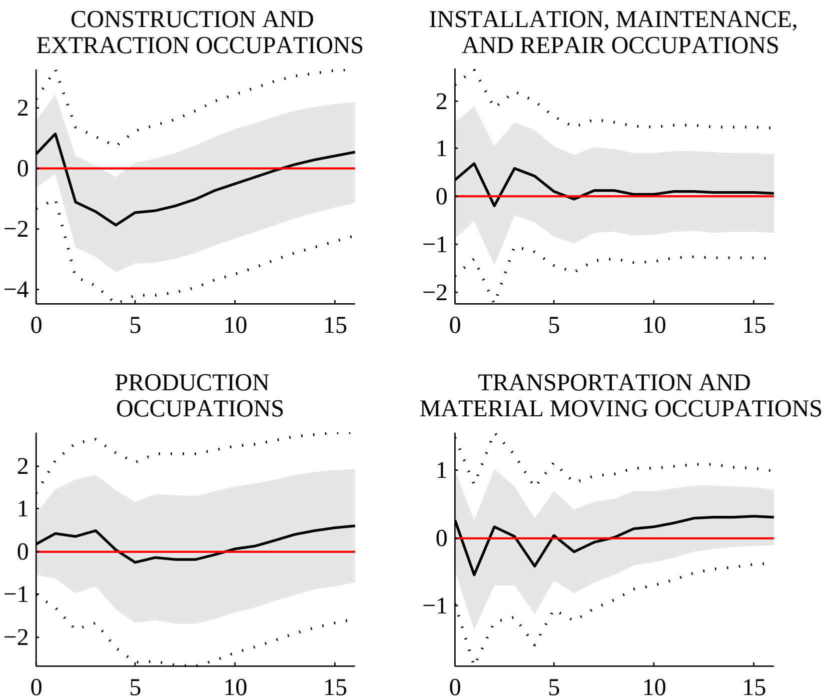
Notes: The solid lines are the impulse responses to a government spending shock. Grey shaded areas and dotted lines show 68 percent and 90 percent confidence bands. The responses are expressed in percentage terms. On the horizontal axes, the horizon is given in quarters. The impact response of output is normalized to one percent.

Figure A3: The effects of government spending shocks on employment in service occupations, sales occupations, and office occupations.



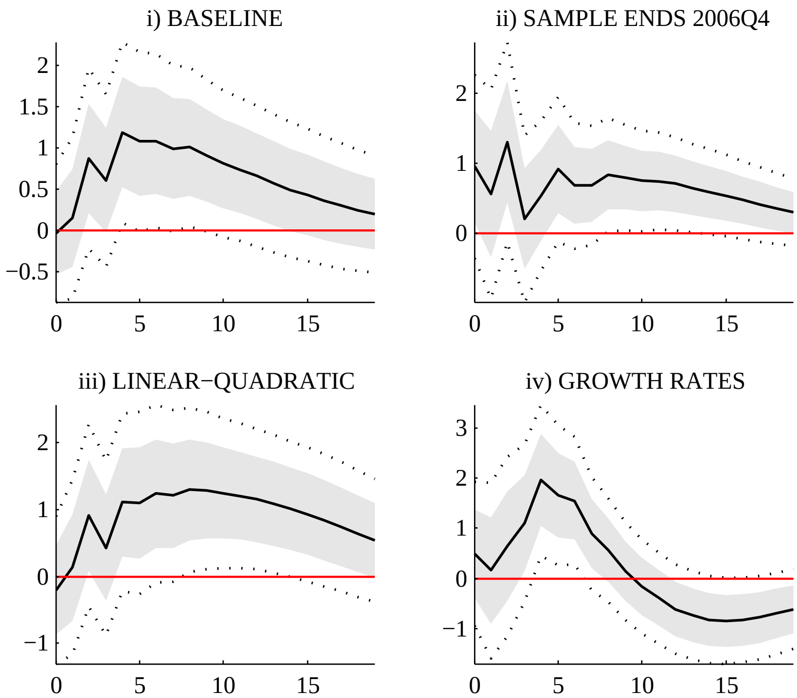
Notes: The solid lines are the impulse responses of employment in the major subcategories of pink-collar occupations to a government spending shock. Grey shaded areas and dotted lines show 68 percent and 90 percent confidence bands. The responses are expressed in percentage terms. On the horizontal axes, the horizon is given in quarters. The impact response of output (not shown) is normalized to one percent.

Figure A4: The effects of government spending shocks on employment in construction and extraction occupations, installation, maintenance, and repair occupations, production occupations, and transportation and material moving occupations.



Notes: The solid lines are the impulse responses of employment in the major subcategories of blue-collar occupations to a government spending shock. Grey shaded areas and dotted lines show 68 percent and 90 percent confidence bands. The responses are expressed in percentage terms. On the horizontal axes, the horizon is given in quarters. The impact response of output (not shown) is normalized to one percent.

Figure A5: The effects of government spending shocks on pink-collar employment relative to blue-collar employment; alternative detrending methods and alternative sample period.



Notes: The solid lines are the impulse responses of the pink-collar to blue-collar employment ratio to a government spending shock. Grey shaded areas and dotted lines show 68 percent and 90 percent confidence bands. The responses are expressed in percentage terms. On the horizontal axes, the horizon is given in quarters. The impact response of output (not shown) is normalized to one percent. Pink collar: service occupations; sales and related occupations; office and administrative support occupations. Blue collar: construction and extraction occupations; installation, maintenance, and repair occupations; production occupations; transportation and material moving occupations.

C.3 Alternative VAR specifications

Figure A5 summarizes the results from various robustness checks for our finding that fiscal expansions lead to a disproportionate increase in the employment of pink-collar occupations relative to blue-collar occupations. Panel i) repeats our baseline specification for the sake of comparison. Our main results are robust to excluding the Great Recession and its aftermath from the sample period, see panel ii) where we re-estimated the model on a sample that ends in 2006q4. Our results are also robust to alternative ways of handling trends in the data. Panel iii) shows the response of the pink-collar to blue-collar employment ratio when the data series have been detrended with a linear-quadratic trend, and Panel iv) refers to the case where the variables enter as year-on-year growth rates.

C.4 Alternative identification of fiscal shocks

Figure A6 shows that the blue-collar to pink-collar employment ratio rises, as in our baseline identification, also when we employ two alternative identification schemes for government spending shocks. The upper left panel shows the response when we measure government spending shocks as innovations to the forecast error of government spending, following Auerbach and Gorodnichenko (2012). To do so, we add the forecast error for the growth rate of government spending, i.e. the difference between the actual, first-release series and the forecasts series, to the set of observables. The forecast error is ordered first and the identification scheme is again recursive.

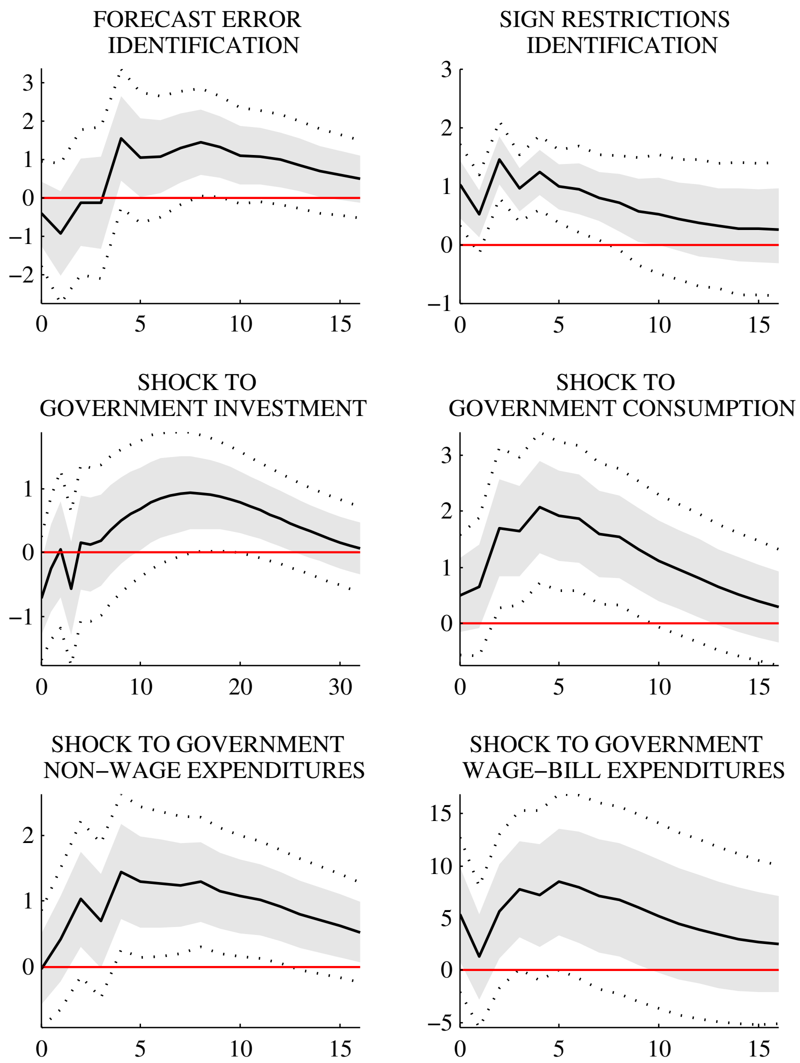
The upper right panel shows the results from an identification using sign restrictions. In particular, we follow Mountford and Uhlig (2009) and Pappa (2009) and identify fiscal shocks by imposing that a government spending shock raises government spending, GDP and the primary budget deficit, and is orthogonal to a business cycle shock (which we also identify).

The middle left and middle right panels in Figure A6 show results from an exercise where we separately identify exogenous variations in government investment and government consumption. In these VARs, we include the series of government investment and government consumption instead of total government spending. Identification of shocks to government investment (consumption) is achieved by ordering the respective variable first in the Cholesky ordering of the VAR. The effects are found to be stronger for variations in government consumption. Most importantly, we find a significant rise in pink-collar relative to blue-collar employment for both components of government spending.[1]

The bottom row of Figure A6 shows results from an exercise where we separately identify exogenous variations in government non-wage expenditures and government wage-bill expenditures. In these VARs, we include the series of government non-wage expenditures and government wage-bill expenditures instead of total government spending. Identification of shocks to government non-wage-bill expenditures is achieved by ordering the respective variable first in the Cholesky ordering of the VAR. The lower left panel shows that the pink-collar to blue-collar employment ratios rises significantly (as in our baseline specification) when we focus on non-wage bill expenditures. The

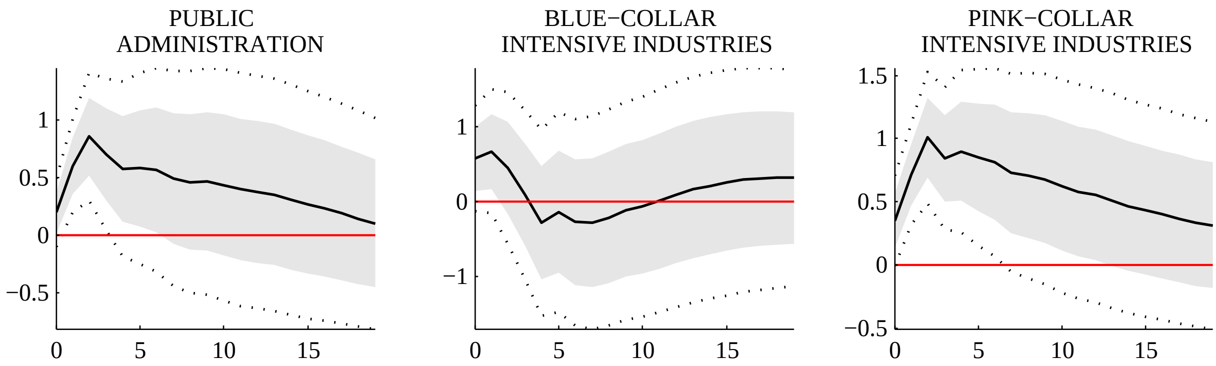
[1] After an innovation to government investment, the rise in the pink-collar to blue-collar employment ratio is more delayed compared to the case of government consumption (which is why we show the respective response over a longer horizon in the figure).

Figure A6: The effects of government spending shocks on pink-collar employment relative to blue-collar employment; alternative identifications.



Notes: The solid lines are the impulse responses of the pink-collar to blue-collar employment ratio to a government spending shock (government investment in the middle left panel, government consumption in the middle right panel, government non-wage expenditures in the lower left panel, government wage-bill expenditures in the lower right panel). Grey shaded areas and dotted lines show 68 percent and 90 percent confidence bands. The responses are expressed in percentage terms. On the horizontal axes, the horizon is given in quarters. The impact response of output (not shown) is normalized to one percent. Pink collar: service occupations; sales and related occupations; office and administrative support occupations. Blue collar: construction and extraction occupations; installation, maintenance, and repair occupations; production occupations; transportation and material moving occupations.

Figure A7: The effects of government spending shocks on employment in the public sector and in broad industry groups.



Notes: The solid lines are the impulse responses of public employment (left panel), of employment in blue-collar intensive industries (middle panel), and of employment in pink-collar intensive industries (right panel) to a government spending shock. Grey shaded areas and dotted lines show 68 percent and 90 percent confidence bands. The responses are expressed in percentage terms. On the horizontal axes, the horizon is given in quarters. The impact response of output (not shown) is normalized to one percent.

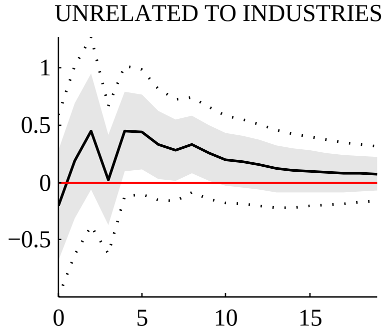
lower right panel displays the results of a shock to wage-bill expenditures. Also in this specification, we observe a significant increase in relative pink-collar employment.

C.5 Between-industry dynamics

Figure A7 displays employment dynamics in specific sectors and industry groups. The left panel shows a surge in public employment after government spending expansions. This surge is only slightly more pronounced than the increase in aggregate employment; the share of public employment in total employment (not shown) rises by only about 0.1 percentage points compared to an average public employment share of about 4.5 percent in our sample. Hence, an expansion of government employment – where pink-collar occupations are over-represented – contributes to the documented occupational employment dynamics but only to a very limited degree.

The middle and right panels of Figure A7 show the employment response in blue-collar intensive and pink-collar intensive industries. We define an industry to be blue-collar intensive if the share of blue-collar workers in this industry is higher than the blue-collar share in aggregate employment. Pink-collar intensive industries are defined analogously. We observe that employment in pink-collar intensive industries responds more strongly and more persistently to government spending expansions than employment in blue-collar intensive industries. Importantly, though, we observe significantly stronger employment growth for pink-collar occupations also *within* these industry groups, see Figure 5 in the main text.

Figure A8: The effects of government spending shocks on pink-collar employment relative to blue-collar employment unrelated to industry dynamics.



Notes: The solid line is the impulse response of the pink-collar to blue-collar employment ratio unrelated to industry dynamics to a government spending shock. The grey shaded area and the dotted lines show 68 percent and 90 percent confidence bands. The responses are expressed in percentage terms. On the horizontal axes, the horizon is given in quarters. The impact response of output (not shown) is normalized to one percent. Pink collar: service occupations; sales and related occupations; office and administrative support occupations. Blue collar: construction and extraction occupations; installation, maintenance, and repair occupations; production occupations; transportation and material moving occupations.

C.6 Occupational employment dynamics unrelated to industry dynamics

In this section, we describe a formal test of the hypothesis that our results are solely reflecting between-industry employment dynamics. We define a hypothetical time series of occupational employment triggered only by industry dynamics: $\hat{o}_t' = S \times i_t'$ where S is the matrix of long-run mean occupation shares in major industries and i_t is the vector of observed employment dynamics in major industries. We then take the difference between the vector of observed occupational employment o_t and the hypothetical occupational employment series: $\varepsilon_t' = o_t' - S \times i_t'$. The residual ε_t is the component of occupational employment dynamics unrelated to industry dynamics. We use all 13 major industries in i_t and a period without re-classifications of occupation- or industry codes in the CPS to determine S. Hence, we can be sure that the results of our test are unaffected by how we group industries or by how we treat re-classifications of industry and occupation variables.

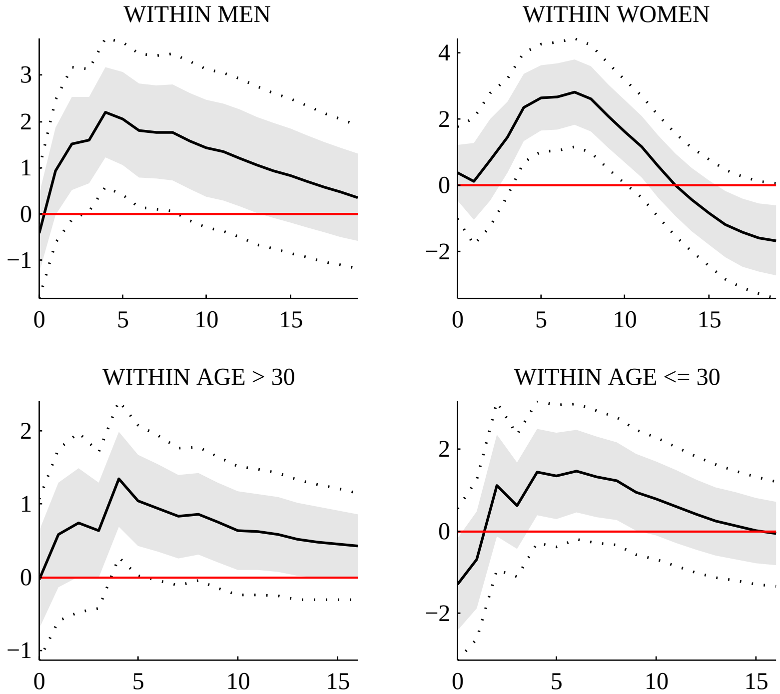
If our documented occupational employment dynamics *were* solely a consequence of industry dynamics, we would not observe any systematic reactions in the occupational employment series which is unrelated to industries, i.e., in ε_t. Figure A8 shows, however, that we do observe a significant shift from blue-collar employment to employment in service, sales, and office occupations also in this component of occupational employment.

From this we conclude that the documented differences in employment dynamics between occupations are due to occupation-specific reasons and not only a consequence of composition effects running from industries to occupations. As a consequence, differences in employment dynamics between industries are then in part a result of occupation-specific reasons through a composition effect running from occupations to industries. Hence, a pure within-industry perspective distills occupational employment dynamics unrelated to industries but understates the importance of occupation-specific factors for economy-wide occupational employment dynamics because it ignores also those between-industry dynamics which are due to occupation-specific reasons. Note that our formal test is constructed in a way diametrically opposed to our own hypothesis. The hypothesis that we want to reject is that there are no occupation-specific employment effects. If this were the case, all observed industry dynamics would be truly driven by industry-specific effects. Notice, however, that – according to our evidence displayed in Figure A8 – there are occupation-specific effects. Thus, some of the industry dynamics displayed in Figure A7 are actually reflecting occupation-specific employment effects due to differences in the occupation-mix across industries. To understand this possibility, consider the following thought experiment. Suppose pink-collar employment grows by 1% in every industry while employment in other occupations stays constant. In this experiment, the percentage employment growth in an industry would be equal to the specific industry's share of pink-collar workers. In the theoretical part of paper, we provide an explanation for occupation-specific employment dynamics based on differences in the substitutability between capital services and labor across occupations. Put differently, the responses shown in Figure A8 exclude all within-industry dynamics and thus also those which are actually driven by occupation-specific dynamics and, hence, understate the true importance of occupations.

C.7 Workers' characteristics

Figure A9 shows occupational employment dynamics by gender and age. In the upper left panel, we only consider males and show that, also in this group, pink-collar employment grows more strongly in response to fiscal expansions than blue-collar employment. The upper right panel shows that the same holds in the group of women. The lower panels show that the pink-collar to blue-collar employment ratio also rises in the group of old workers aged 30 and above (left panel) and in the group of young workers aged below 30 (right panel), respectively. These results are important since one may argue that occupational employment dynamics are simply reflecting gender-specific or age-

Figure A9: The effects of government spending shocks on pink-collar employment relative to blue-collar employment within gender and within age groups.



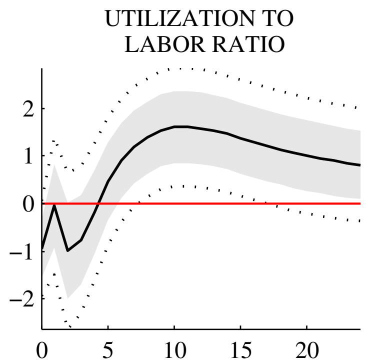
Notes: The solid lines are the impulse responses of the pink-collar to blue-collar employment ratio to a government spending shock. Grey shaded areas and dotted lines show 68 percent and 90 percent confidence bands. The responses are expressed in percentage terms. On the horizontal axes, the horizon is given in quarters. The impact response of output (not shown) is normalized to one percent. Pink collar: service occupations; sales and related occupations; office and administrative support occupations. Blue collar: construction and extraction occupations; installation, maintenance, and repair occupations; production occupations; transportation and material moving occupations.

specific employment dynamics due to, first, different gender or age shares across occupations and, second, gender or age differences in labor-supply elasticities or attachments to the labor market. If our results were solely driven by, e.g., women raising their labor supply after fiscal expansions, we would also observe a rise in the aggregate pink-collar to blue-collar employment ratio due to a composition effect. We would, however, not observe an increase in the pink-collar to blue-collar employment ratio within the groups of men and women, respectively. Hence, the observation of occupational employment dynamics within gender allows to reject the hypothesis that the aggregate occupational employment dynamics are just a reflection of gender-specific employment dynamics. A similar argument applies to age.

C.8 Capital utilization

In our model, firms increase their demand for pink-collar labor by more than their demand for blue-collar labor after a government spending expansion due to substitution away from labor towards a more intensive use of capital. We now provide direct empirical evidence for this substitution between factors. We do so by including data on the capital utilization to labor ratio in our baseline VAR. Since capital utilization is not directly observable, we follow Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramirez (2015) and use the series 'Capacity Utilization: Total Industry' from the Board of Governors of the Federal Reserve System as a proxy for capital utilization. Labor is measured in a way that is consistent with our model, i.e., as total hours worked by workers in pink-collar and blue-collar occupations.[2] We re-estimate our baseline VAR with the utilization to labor ratio as seventh variable. Figure A10 shows a significant increase in this ratio, in line with the prediction of our theoretical model.

Figure A10: The effect of government spending shocks on the utilization-labor-ratio.



Notes: The solid line is the impulse responses of the utilization to labor ratio to a government spending shock. Grey shaded areas and dotted lines show 68 percent and 90 percent confidence bands. The responses are expressed in percentage terms. On the horizontal axes, the horizon is given in quarters. The impact response of output (not shown) is normalized to one percent.

[2]We obtain similar results when we also include white-collar workers.

D Model appendix

This model appendix derives, first, the analytical solution of the simplified model discussed in Section 4.2 of the main text. Second, it presents additional model results discussed in Section 4.4.

D.1 Simplified model

Applying the parameter restrictions discussed in the main text, the set of equilibrium conditions simplifies to the following system where a dash attached to the equation number indicates the simplified version of the respective equation in the main text:

$$
\begin{aligned}
y_{j,t} &= z \cdot \left(\left(\frac{1}{2} \cdot \tilde{k}_{j,t}^{\frac{\phi-1}{\phi}} + \frac{1}{2} \cdot \left(a_t \cdot n_{j,t}^{b} \right)^{\frac{\phi-1}{\phi}} \right)^{\phi/(\phi-1)} \right)^{1/2} \left(a_t \cdot n_{j,t}^{p} \right)^{1/2}, && (2') \\
\log a_t &= \log a + \varepsilon_t^{a} \\
r_t^{k} &= \frac{1}{4} \cdot z \cdot mc_t \cdot \left(\frac{1}{2} \cdot \tilde{k}_t^{\frac{\phi-1}{\phi}} + \frac{1}{2} \cdot \left(a_t n_t^{b} \right)^{\frac{\phi-1}{\phi}} \right)^{\phi/2(\phi-1)-1} (a_t n_t^{p})^{1/2} \, \tilde{k}_t^{-1/\phi}, && (4') \\
w_t^{b} &= \frac{z}{4} mc_t a_t \left(\frac{1}{2} \tilde{k}_t^{\frac{\phi-1}{\phi}} + \frac{1}{2} \left(a_t n_t^{b} \right)^{\frac{\phi-1}{\phi}} \right)^{\phi/2(\phi-1)-1} \cdot (a_t n_t^{p})^{1/2} \cdot \left(a_t n_t^{b} \right)^{-1/\phi}, && (5') \\
w_t^{p} &= \frac{1}{2} \cdot mc_t \cdot (y_t / n_t^{p}), && (6') \\
\psi(\pi_t - 1)\pi_t &= \psi\beta \, \mathrm{E}_t \left\{ \frac{\lambda_{t+1}}{\lambda_t} \frac{y_{t+1}}{y_t} (\pi_{t+1} - 1)\pi_{t+1} \right\} + \epsilon \left(mc_t - \frac{\epsilon - 1}{\epsilon} \right), && (7') \\
\lambda_t &= \left(c_t - \left(\frac{\Omega^{p}}{2} (n_t^{p})^2 + \frac{\Omega^{b}}{2} (n_t^{b})^2 \right) \right)^{-1}, && (13') \\
\lambda_t &= \beta \, \mathrm{E}_t \left\{ \lambda_{t+1} \frac{(1 + r_t)}{\pi_{t+1}} \right\}, && (15') \\
(1-\tau) r_t^{k} &= \delta_1 + \delta_2 (u_t - 1), && (18') \\
(1-\tau) w_t^{b} &= \Omega^{b} n_t^{b}, && (19') \\
(1-\tau) w_t^{p} &= \Omega^{p} n_t^{p}, && (20') \\
\log \left(\frac{1 + r_t}{1 + r} \right) &= \delta_\pi \log (\pi_t / \pi) && (21') \\
\log g_t &= \log g + \varepsilon_t^{g} \\
y_t &= c_t + g_t + e_t (u_t) \, k_t, && (23')
\end{aligned}
$$

which uses that $\chi = 0$ implies $x_t = x_{t-1} = x$ which we normalize to one and that $\kappa_i \to \infty$ together with $\delta = 0$ imply that the stock of physical capital is constant, i.e. $k_t = k_{t-1} = k$, and hence $\widetilde{k}_t = k \cdot u_t$.

In log-linear terms, we obtain the following system where a double dash attached to the equation number indicates the log-linearization of the respective simplified equilibrium condition:

$$\widehat{y}_t = \frac{1}{4} \cdot \left(\widehat{u}_t + \widehat{a}_t + \widehat{n}_t^b\right) + \frac{1}{2} \cdot (\widehat{a}_t + \widehat{n}_t^p)\,, \tag{2”}$$

$$\widehat{a}_t = \varepsilon_t^a$$

$$\widehat{r}_t^k = \widehat{mc}_t - \frac{2+\phi}{4\phi}\widehat{u}_t + \frac{2+\phi}{4\phi} \cdot \widehat{a}_t + \frac{2-\phi}{4\phi} \cdot \widehat{n}_t^b + \frac{1}{2} \cdot \widehat{n}_t^p\,, \tag{4”}$$

$$\widehat{w}_t^b = \widehat{mc}_t + \frac{2-\phi}{4\phi} \cdot \widehat{u}_t + \frac{5\phi-2}{4\phi} \cdot \widehat{a}_t - \frac{2+\phi}{4\phi}\widehat{n}_t^b + \frac{1}{2} \cdot \widehat{n}_t^p, \tag{5”}$$

$$\widehat{w}_t^p = \widehat{mc} + \frac{1}{4} \cdot \left(\widehat{u}_t + \widehat{a}_t + \widehat{n}_t^b\right) + \frac{1}{2} \cdot \widehat{a}_t - \frac{1}{2}\widehat{n}_t^p, \tag{6”}$$

$$\widehat{\pi}_t = \beta\, \mathrm{E}_t\, \widehat{\pi}_{t+1} + \kappa \cdot \widehat{mc}_t\,, \tag{7”}$$

$$\lambda^2 \cdot \widehat{\lambda}_t = -\widehat{c}_t + \Omega^p \cdot \widehat{n}_t^p + \Omega^b \cdot \widehat{n}_t^b\,, \tag{13”}$$

$$\widehat{\lambda}_t = \mathrm{E}_t\, \widehat{\lambda}_{t+1} + \widehat{R}_t - \mathrm{E}_t\, \widehat{\pi}_{t+1}\,, \tag{15”}$$

$$\widehat{r}_t^k = \Delta^{-1} \cdot \widehat{u}_t\,, \tag{18”}$$

$$\widehat{w}_t^b = \widehat{n}_t^b\,, \tag{19”}$$

$$\widehat{w}_t^p = \widehat{n}_t^p\,, \tag{20”}$$

$$\widehat{R}_t = \delta_\pi \widehat{\pi}_t \tag{21”}$$

$$\widehat{g}_t = \varepsilon_t^g,$$

$$\widehat{y}_t = \frac{c}{y}\widehat{c}_t + \frac{g}{y}\widehat{g}_t + \frac{\delta_1}{y}\widehat{u}_t, \tag{23”}$$

where $\kappa = (\varepsilon - 1)/\psi$ is the slope of the linearized Phillips curve, and $R_t = 1 + r_t$.

We combine conditions (4”), (5”), (6”), (18”), (19”), and (20”) and obtain the following factor market clearing conditions:

$$\left(\Delta^{-1} + \frac{2+\phi}{4\phi}\right) \cdot \widehat{u}_t = \widehat{mc}_t + \frac{2+\phi}{4\phi} \cdot \widehat{a}_t + \frac{2-\phi}{4\phi} \cdot \widehat{n}_t^b + \frac{1}{2} \cdot \widehat{n}_t^p, \tag{1}$$

$$\frac{2+5\phi}{4\phi} \cdot \widehat{n}_t^b = \widehat{mc}_t + \frac{2-\phi}{4\phi} \cdot \widehat{u}_t + \frac{5\phi-2}{4\phi} \cdot \widehat{a}_t + \frac{1}{2} \cdot \widehat{n}_t^p, \tag{2}$$

$$\frac{3}{2} \cdot \widehat{n}_t^p = \widehat{mc}_t + \frac{1}{4} \cdot \left(\widehat{u}_t + \widehat{a}_t + \widehat{n}_t^b\right) + \frac{1}{2} \cdot \widehat{a}_t. \tag{3}$$

Further, the absence of serial correlations in the disturbances and endogenous state variables implies

$\mathrm{E}_t\,\widehat{\pi}_{t+1} = \mathrm{E}_t\,\widehat{\lambda}_{t+1} = 0$ which allows to combine conditions (7"), (13") (15"), (21"), and (23") to

$$\frac{y}{c}\cdot\widehat{y}_t - \frac{g}{c}\cdot\widehat{g}_t - \frac{\delta_1}{c}\cdot\widehat{u}_t = \Omega^p\cdot\widehat{n}_t^p + \Omega^b\cdot\widehat{n}_t^b - \Gamma\cdot\widehat{mc}_t, \tag{4}$$

where $\Gamma = \delta_\pi\cdot\kappa\cdot\lambda^2 > 0$.

Together with the linearized production function (2"), (1)-(3) and (4) form a system in five equations and five endogenous variables each period. In this system, $\widehat{u}_t$, $\widehat{n}_t^b$, $\widehat{n}_t^p$, $\widehat{y}_t$, and $\widehat{mc}_t$ are endogenous while $\widehat{g}_t = \varepsilon_t^g$ and $\widehat{a}_t = \varepsilon_t^a$ are determined exogenously. Since there is no persistence, the system of linear equations is static in each period and can be solved for the following equations for output and both types of labor:

$$\widehat{y}_t = \Lambda^{-1}\left(\Delta^{-1} + 3\phi + 5\Delta^{-1}\phi + 7\right) g\cdot\widehat{g}_t + \xi_{y,a}\cdot\widehat{a}, \tag{5}$$

$$\widehat{n}_t^b = \Lambda^{-1}\left(8\Delta^{-1}\phi + 8\right) g\cdot\widehat{g}_t + \xi_{b,a}\cdot\widehat{a}_t, \tag{6}$$

$$\widehat{n}_t^p = \Lambda^{-1}\left(2\Delta^{-1} + 2\phi + 6\Delta^{-1}\phi + 6\right) g\cdot\widehat{g}_t + \xi_{p,a}\cdot\widehat{a}_t, \tag{7}$$

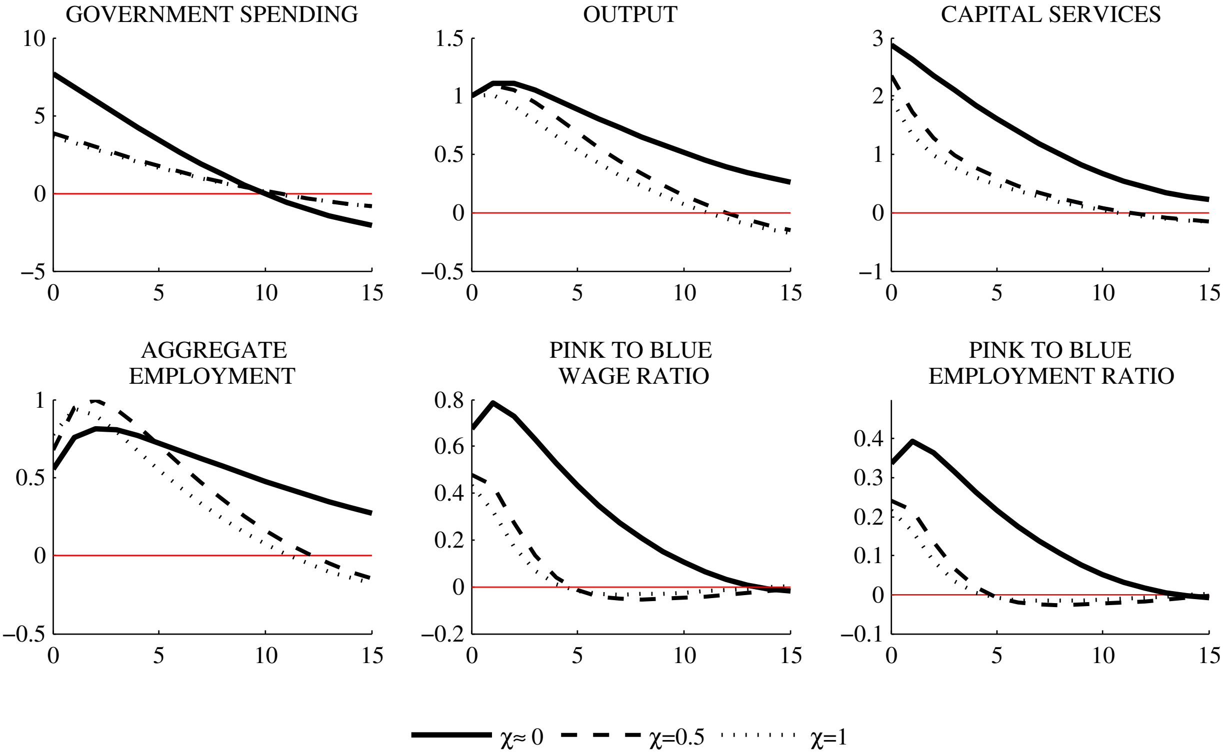
where Λ is defined as in the main text and $\xi_{y,a} = \Lambda^{-1}\cdot(\Gamma\cdot(1-g/y)\cdot(2\Delta^{-1}+2\phi+10\Delta^{-1}\phi+10) + \frac{1}{8}\cdot\frac{\varepsilon-1}{\varepsilon}\cdot(1-g/y)\cdot(2\phi-11\Delta^{-1}-38-25\Delta^{-1}\phi) - \frac{1}{2}\frac{\varepsilon-1}{\varepsilon}(1+5\phi))$, $\xi_{b,a} = \Lambda^{-1}\cdot(\Gamma\cdot(1-g/y)\cdot(5+\phi+9\Delta^{-1}\phi-3\Delta^{-1}) + 2\cdot\frac{\varepsilon-1}{\varepsilon}\cdot(1-\phi) + (1-g/y)\cdot\frac{\varepsilon-1}{\varepsilon}\cdot\Delta^{-1}\cdot(1+\Delta)\cdot(1-\phi) + 3\phi - 9 - \Delta^{-1} - 5\Delta^{-1}\phi)$, and $\xi_{p,a} = \Lambda^{-1}\cdot(\Gamma\cdot(1-g/y)\cdot(\Delta^{-1}+\phi+5\Delta^{-1}\phi+5) + \frac{\varepsilon-1}{\varepsilon}\cdot(1-\phi) - \frac{1}{2}\cdot(1-g/y)\cdot\frac{\varepsilon-1}{\varepsilon}\cdot\Delta^{-1}\cdot(1+\Delta)\cdot(1-\phi) - 5 - \phi - \Delta^{-1} - 5\Delta^{-1}\phi)$. Setting $\widehat{a}_t = 0$ yields equation (24) in the main text and subtracting (6) from (7) gives equation (25) in the main text.

D.2 Additional model results

We present two additional model results. First, we demonstrate that, qualitatively, our results do not hinge on how we parameterize the wealth effect on labor supply. Second, we show that labor productivity shocks lead to a *decline* in the pink-collar to blue-collar employment ratio.

Wealth elasticity. Figure A11 displays results for alternative values of the wealth elasticity of labor supply. As discussed in Section 4.4, a stronger wealth effect on labor supply (i.e., an increase in the parameter χ) dampens the impact of a spending shock on the employment ratio, see Figure A11. Notice, however, that the employment ratio rises even in the limiting case $\chi = 1$.

Figure A11: Model-implied impulse responses to a government spending shock for different wealth elasticities.



Notes: The responses are expressed in percentage terms. On the horizontal axes, the horizon is given in quarters. The size of the innovation is normalized such that the response of output (not shown) is one percent on impact.

Labor productivity shocks. In the simplified model version, the effects of an innovation to labor productivity, a_t, are not unambiguous but depend on the slope of the Phillips curve as measured by the composite parameter κ. If the Phillips curve is not too flat, i.e., κ not too small, a positive labor productivity shock raises output and aggregate employment but lowers the pink-collar to blue-collar employment ratio provided that blue-collar labor is a closer substitute to capital services than pink-collar labor. To demonstrate this, consider the limiting cases $\epsilon \to \infty$ (perfect competition) or $\psi \to 0$ (no price adjustment costs) which both lead to $\kappa \to \infty$.

In the limiting case where $\kappa \to \infty$, condition (7") implies $\widehat{mc}_t = 0$ such that conditions (2") and (1)-(3) form a system in four equations and four endogenous variables, $\widehat{u}_t$, $\widehat{n}_t^b$, $\widehat{n}_t^p$, and $\widehat{y}_t$ while $\widehat{mc}_t = 0$ and $\widehat{a}_t = \varepsilon_t^a$ is determined exogenously. Solving the static system of linear equations in each period yields

$$\widehat{y}_t = \frac{2\Delta^{-1} + 2\phi + 10\Delta^{-1}\phi + 10}{3\Delta^{-1} + \phi + 7\Delta^{-1}\phi + 5} \cdot \widehat{a}_t, \tag{8}$$

and

$$\widehat{n}_t^b = \frac{5 + \phi + 9\Delta^{-1}\phi - 3\Delta^{-1}}{3\Delta^{-1} + \phi + 7\Delta^{-1}\phi + 5} \cdot \widehat{a}_t, \tag{9}$$

$$\widehat{n}_t^p = \frac{\Delta^{-1} + \phi + 5\Delta^{-1}\phi + 5}{3\Delta^{-1} + \phi + 7\Delta^{-1}\phi + 5} \cdot \widehat{a}_t. \tag{10}$$

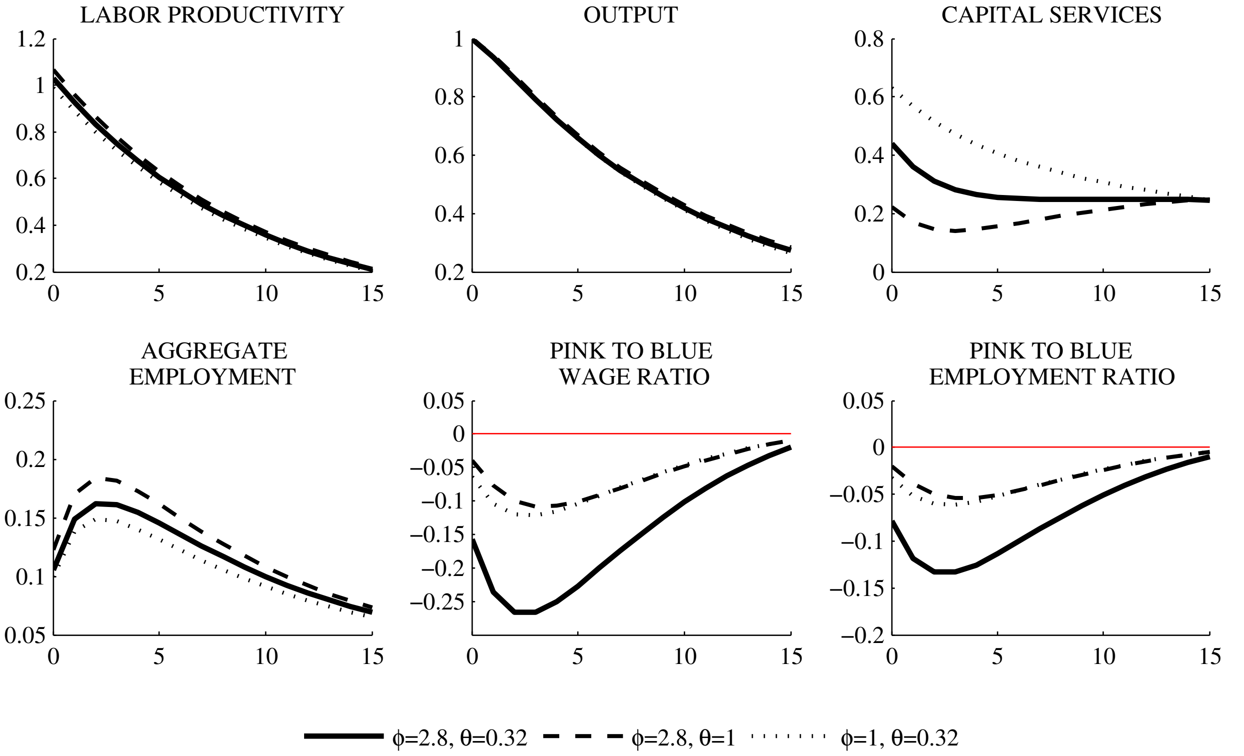
Subtracting (9) from (10) gives

$$\widehat{n_t}^p - \widehat{n_t}^b = \frac{4}{3 + \Delta\phi + 7\phi + 5\Delta} \cdot (1 - \phi) \cdot \widehat{a}_t. \tag{11}$$

Output rises unambiguously in $\widehat{a}$. If blue-collar labor is a closer substitute to capital services than pink-collar labor ($\phi > 1$), the pink-collar to blue-collar employment ratio falls in response to a positive labor productivity shock ($\widehat{a} > 0$, $\widehat{g} = 0$). The intuition is as follows. As labor becomes more productive, firms increase their demand for capital services by less than their effective labor input, i.e., the product of labor productivity and aggregate employment. With relatively less capital services used, the marginal productivity of the substitute blue-collar labor increases relative to pink-collar labor. Hence, firms raise their demand for blue-collar labor relative to pink-collar labor.

Similar relations also hold for less restrictive assumptions concerning the slope of the Phillips

Figure A12: Model-implied impulse responses to labor productivity shock.



Notes: The responses are expressed in percentage terms. On the horizontal axes, the horizon is given in quarters. The size of the innovation is normalized such that the response of output (not shown) is one percent on impact.

curve. By continuity, there exists a $\kappa^* < \infty$ such that the following results hold: If blue-collar labor is a closer substitute to capital services than pink-collar labor ($\phi > 1$) and the Phillips curve is sufficiently steep ($\kappa > \kappa^*$), a positive labor productivity shock also raises output and aggregate employment but reduces the pink-collar to blue-collar employment ratio.

Figure A12 shows impulse responses to an innovation in labor productivity obtained using the calibrated full model. As for fiscal shocks, we show results for three different parameterizations of the elasticities of substitution in production. In response to an increase in labor productivity a_t, employment in blue-collar occupations rises disproportionately. The larger is the ratio of ϕ and θ, the stronger is the gap in the degree of substitutability with capital services across occupations and, thus, the stronger is the increase in blue-collar employment.

To sum up, a favorable labor productivity shocks leads to stronger employment growth for blue-collar workers relative to pink-collar workers and thus leads to diametrically opposite occupational employment dynamics compared to government spending expansions.