Immigration, Demand, Supply and Sectoral Heterogeneity in the UK Labor Market*

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Abstract

The empirical migration literature has often identified the labor market effects of immigration using variation of immigration concentration across regions or sectors. However, this approach overlooks macroeconomic effects which occur in all regions and sectors. Instead, we estimate the relative contributions of competing macroeconomic and sectoral demand, supply and immigration effects, by applying a VAR approach to UK labor market variables for 35 different sectors from 2001-2019. We find that, while immigration is in part endogenously determined by supply and demand, most of the evolution in aggregate migration share over the sample period is driven by the identified exogenous aggregate migration process. This then plays a significant negative role in the determination of native aggregate wage growth. Historical decompositions, which decompose both the error terms and, novelly, the constant terms into their structural parts, reveal that other aggregate processes have offsetting effects which account for the weak observed association between wages and immigration observed in the data. We also find substantial heterogeneity in the responses of wages and hours to sector specific shocks. (173 words)

Keywords: Immigration, Demand, Supply, VAR, Sectoral Heterogeneity

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1 Introduction

Immigration is, in part, a macroeconomic phenomenon. Foreign born labor currently accounts for nearly 20% of the UK workforce and averages around 15% across OECD economies.[1] The empirical migration literature often identifies the labor market effects of immigration using the variation of immigration concentration across regions or sectors. However this approach obscures the effects of macroeconomic shocks which occur in all regions and sectors. In this paper we use macroeconomic time series methods to identify, for the first time, the macroeconomic impacts of immigration alongside sector specific contributions to provide a new perspective on the labor market effects of immigration.

While the effect of immigration on the labor market is of intrinsic economic interest, it is also the focus of longstanding political attention, with immigration linked empirically to the rise of counter-globalization voting patterns across the world, see Rodrik (2021) and Docquier et al (2026). In this context, establishing whether there may exist adverse labor market effects associated with immigration becomes an even more important concern. The empirical literature to date has consistently found only small effects of immigration on native wages.[2] Manacorda, Manning, and Wadsworth (2012), and Ottoviano and Peri (2012) offer imperfect substitutability of immigrant and native labor as one possible explanation for these small wage effects. We argue that wages, hours and indeed immigration, are determined simultaneously in a labor market subject to multiple shocks at the aggregate and sectoral level. Thus, for example, the observed weak association between wages and immigration may be due to a negative association between wage growth and immigration being offset by a positive association between immigration, wages and aggregate labor demand. By the same token, effects which have been attributed to migration may in fact be the result of other shocks to the system.

The UK labor market is a good subject for our analysis, as it has experienced large variations in immigration rates, wages and employment over time and across sectors. Our analysis employs a vector autoregression (VAR) approach which models immigration as part of a multivariate stochastic process evolving throughout the sample period. This contrasts with much of the literature which models immigration as an assumed exogenous shock to labor supply.

Moreover, even if immigration at the aggregate level is driven by an exogenous shock, immigration at the sectoral level may not be exogenous. Migrants will tend to flow to those sectors with high demand for their labor all else being equal. Sectors will also likely differ for supply side reasons such as, technological change and their use of different types of labor. Therefore to analyze the labor market effects of immigration one also needs to take account of likely sectoral heterogeneity as well as the multiplicity of shocks.

It has long been acknowledged that modeling immigration solely as a labor supply shock has limitations. The potential importance of demand has long been noted by e.g. Borjas

[1] See for example OECD https://www.oecd.org/en/topics/economic-impact-of-migration.html.

[2] See for example Borjas (2004), or Ottoviano and Peri (2012) for the United States or Dustmann, Frattini and Preston (2013), and Manacorda, Manning, and Wadsworth, (2012) for the UK).

(1994), Ottoviano and Peri (2012) and Peri, Rury and Wiltshire (2023) and the dangers of abstracting away from productivity shocks is noted by Dustmann, Schönberg, and Stuhler (2016) and Campo et al (2018). Separately the existing literature has also acknowledged the possibility of heterogeneous effects of immigration across migrant skill level or geographical origin, see e.g. Dustmann et al (2016), Ottoviano and Peri (2012) and Manacorda, Manning, and Wadsworth, (2012).

In this paper we follow the literature and identify an exogenous migration shock, but, unlike the existing literature, we also identify demand and productivity shocks at the aggregate and sectoral levels which may also determine migration. With respect to heterogeneity, we follow Mountford and Wadsworth (2023) in distinguishing between skill levels across industries.[3] Our analysis shows that demand, productivity shocks and sectoral heterogeneity have important roles in explaining the evolution of the UK labor market.

We employ a six variable VAR using UK data from 2001-2019 for each of 35 different labor market sectors to identify demand, supply and immigration effects on key labor market outcomes of interest at both the aggregate and sectoral level. The six variables are the economy-wide migration share, hours worked and real wage of natives, along with the same variables for each sector. These six variables permit the identification of the three aggregate and three sectoral shocks which occur simultaneously in every time period. There is thus potential for these effects to either offset or complement each other. The combination of aggregate and sectoral variables in the same VAR echoes the approach of Canova (2005) in modeling the effects of US shocks on smaller Latin American economies and Mumtaz and Surico (2009) on the effects of international shocks on the domestic (UK) economy.

We identify shocks using sign restrictions, an approach that has been frequently used in the macroeconomic literature, notably by Canova and De Nicoló (2002), Uhlig (2005), Mumtaz and Surico (2009) and Baumeister and Hamilton (2015, 2019, 2024) and applied to immigration by Furlanetto and Robstad (2019) and Kiguchi and Mountford (2017). In this paper we follow the particular approach of Baumeister and Hamilton (2015, 2019, 2024) who show how sign restrictions can be imposed as part of a more general framework where beliefs and incomplete information about the parameters of a structural model can be incorporated into a Bayesian estimation procedure. Uniquely, we extend the analysis to the contributions of the structural constant terms which, as we show below, play a large role in the evolution of the time series. We discuss our choice of sign restrictions in section 3 but our aim is to impose minimal restrictions which are consistent with economic theory so that, for example, an aggregate labor demand shock is identified with the restriction that it has a positive co-movement of native aggregate wages and hours, in contrast to productivity shocks where the co-movement is negative.[4]

[3] Mountford and Wadsworth (2023) find that the effects of skilled immigration on training of the native workforce differs significantly across sectors, with negative effects of immigration on native training in the skilled non-traded sectors and positive effects in the traded sector. They attribute this to the limited ability of the non-traded sector to increase output in response to supply shocks compared to the traded sector.

[4] As discussed in section 5, one can impose stronger sign restrictions restrictions or impose sign restrictions on more than one period using the penalty function approach as in Uhlig (2005) and Mountford and Uhlig

The imposed sign restrictions are intuitive in and of themselves, but their plausibility is reinforced by the associated historical decompositions of the aggregate time series into the contributions of the three aggregate structural equations. The exogenous aggregate migration equation explains most of the evolution in the aggregate migration share with a strong negative shock after Brexit. Aggregate labor demand is also significant for migration, with a strong negative shock on migration after the 2008 financial crisis. However, clearly, there are other ways to decompose the data and in section 5 below we discuss the robustness of the result to different identification schemes including different Cholesky orderings and to identification using the penalty function approach. We focus our attention on the analysis of the aggregate equations, because in the main they are more important for explaining the evolution of migration share wages and hours, and because they are easier to identify. However the aggregate equations do not completely explain the evolution of the data. That part of the evolution of the time series not explained by the identified aggregate equations must therefore be explained at the sectoral level. As we show below this can be substantial in some sectors.

We evaluate the extent of the wage effects of each identified aggregate structural equation using a counterfactual approach, where the contribution of one of the structural equations is set to zero in an otherwise standard historical decomposition analysis. This exercise shows the estimated contribution of the left out structural equation to the observed time series. This is done without reference to a deep structural model and so should not be interpreted as performing a 'pseudo experiment'. Rather, this counterfactual is simply a different presentation of the standard historical decomposition to quantify the contribution of a specific structural equation over the sample period.

The VAR framework has been previously used to study the effects of migration most notably by Blanchard and Katz (1992) for internal migration, and more recently by Furlanetto and Robstad (2019) on Norwegian data who also identify other macroeconomic shocks including a business cycle shocks using sign restrictions. Recently Furlanetto, Robstad and Samad (2025), have also extended the VAR approach to incorporate microdata using a Factor Augmented VAR to estimate the effects of immigration shocks at all percentiles of the Norwegian income distribution and find significant heterogeneities across income percentiles. This is consistent with our analysis of heterogeneity across sectors.

The paper is organized as follows. We first describe the data that underpin the analysis in section 2, highlighting the sectoral variation in native wage and immigration growth over the sample period in section 2.1. Section 3 outlines the estimated models and the identification methods used to generate the impulse response functions, historical decompositions and counterfactual time series for immigration and native wages, which are presented in section 4.

(2009) but we focus here on minimal assumptions.

2 Data and motivation

In order to estimate our VAR models we need aggregate and sectoral level data on the total hours worked, wages of UK-born workers and the concentration of working immigrants. The requisite information is contained in the UK Labour Force Survey (LFS). The LFS is a quarterly random sample of around 40,000 households and the individuals therein. We use data starting in the first quarter of 2001 and end our sample in the last quarter of 2019 so as not to include data subject to the effects of the COVID pandemic.[5]

The LFS contains details of the country of birth of every individual in the sample. An immigrant is defined as anyone who is born outside the UK. The LFS also gives the 3-digit industry and occupation codes of employed workers. Since specific industries contain many occupations and a given occupation can be found across different industries, the definition of a sector in our analysis combines individual occupation and industry affiliation. Sample size constraints determine that a sector is built as a combination of four possible occupations, (Professional/Managerial, Other Non-Manual, Skilled Manual and Other Manual), and 13 industries.[6] For example, in our data, sector 112 is a professional (1-digit SOC code = 1) working in the health industry, (2-digit SIC code = 12). One complication with pooling LFS data over time is that the occupational codes change approximately every 10 years.[7] The industry classifications also change in 2009 but we are able to correct for this using the mapping of Smith.[8] We collate the data by sector for each quarter in each year. This ensures that there is a minimum of 100 observations in each of 35 sectors in each quarter with a median sample cell size of 1122 for hours and 267 for native wages. The hours variable we use in our analysis is 'Total Hours Worked', in the survey reference week which includes paid and unpaid overtime. We observe hourly native wages for 40% of the survey respondents and use the median of this at the sectoral level deflated by the CPI price index.[9] The aggregate versions of these variables are grossed up by their LFS population weights.

2.1 Sectoral variation in immigrant labor

The data illustrate the degree of heterogeneity in the sectoral labor market across sectors with respect to immigration in Figure 1. Figure 1a graphs the 18-year change in employment of both UK-born workers and immigrants in each of the 35 sectors in the data set. The backward sloping 45 degree line separates occupations that experience net growth in employment in this

[5] The LFS sample response rates also decline significantly during the pandemic which adversely affects data analysis using disaggregated units.

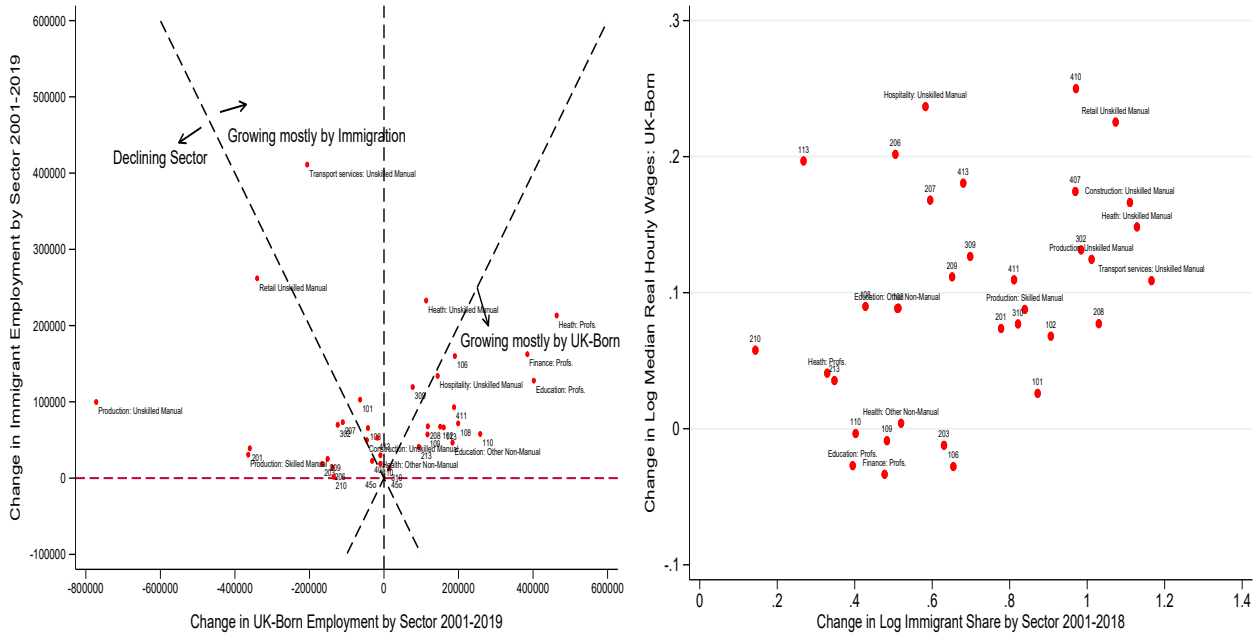
[6] Production, Construction, Retail, Transport, Food & Hospitality, Media&IT, Finance, Scientific, Transport&Support Services, Public Admin, Education, Health , Other Services.

[7] The latest industry re-coding was 2008 and there were 2010 and 2020 re-coding for occupations. The occupational classifications also change much more significantly in 2001, which makes matching before this period difficult. Using 4 broad occupation codes facilitates comparability over time.

[8] The change in the industry codes is less substantial, see https://warwick.ac.uk/fac/soc/economics/staff/jcsmith/sicmapping/

[9] The LFS only elicits wage information from 40% of each sample in every quarter.

Figure 1: Sectoral heterogeneity and immigration in UK labor market 2001-2019



(a) Change in UK-Born & Immigrant Employment by Sector 2001-2019

(b) Log change in UK-born log real hourly wage & immigrant employment share by sector

Figure 1 illustrates the sectoral heterogeneity in the UK labor market. Figure 1a plots the growth of employment of UK-born and immigrant by sector from 2001-2019. Some sector's employment growth has predominantly been through immigrant labor, othesr predominantly through UK-born labor and others more equally determined. Figure 1b plots the growth of native wages against immigrant employment share from 2001-2019 which shows a generally positive relationship but with significant variation.

period from those that are declining. Any occupation that lies above and to the right of this line is growing. The forward sloping 45 degree line separates occupations that are growing primarily because of immigration - those sectors above the line - from those that are growing mainly due to growth in UK-born employment - those sectors below the line. The figure shows that most sectors grow over this period, but a minority decline (e.g. Unskilled Manual in Production or Unskilled Manual in Retail). In all these declining sectors, the number of immigrants rises while the number of UK-born workers falls. This means that the share of immigrants has risen in all sectors with a net decline in employment.[10] Of the sectors with net employment growth over the period, some grow exclusively because of rising immigrant numbers, (e.g. Transport services: Unskilled Manual) while numbers of UK-born employed fall. Others grow through approximately equal numbers of immigrants and UK-born, (e.g. Unskilled workers in Hospitality) and some grow primarily, though not exclusively, through rising numbers of UK-born workers, (e.g. Education Professionals). There is no sector in which the level of immigration falls over this period. Overall Figure 1a shows that there is substantial heterogeneity in changes in both employment and the immigrant share across

[10] This finding also indicates that the immigrant share, a common measure of immigrant concentration in the literature, can also change because of changes in the size of the native workforce.



Figure 2: Growth rates of immigration share, hours worked and average native real wages in the UK 2001-2020. We have used red lines for all the data series in the figures in this paper.

sectors over the sample period. This suggests that different sectors are subject to different shocks and/or they react differently to a given shock.

Figure 1b indicates another facet of heterogeneity of experience across sectors by plotting the change in (log) native wages of UK-born workers in each sector over the sample period against the change in the sectoral log immigrant share. For a given change in immigrant share, the graph shows a large variation in wage growth across sectors. In some sectors native wages fall, while in other sectors, for the same immigrant change, native wages rise. Again this suggests that the association between immigration and the labor market experience of native-born workers is unlikely to be the same in all sectors. However, despite this heterogeneity, there does appear to be a positive relationship overall between changes in immigration and native wages. In our analysis below we decompose the extent to which this is caused by supply and demand factors in each sector.

2.1.1 Granger causality

The idea that the amount of immigrant labor employed in an economy will depend on the demand for and supply of labor is extremely intuitive. Figure 2 plots the year on year growth rates of the share of immigrants in the working age population, the total number of hours worked and the average real wage of natives between 2001(Q1)-2019(Q4). The time series appear related most noticeably after the financial crisis of 2007-2008 and the subsequent recovery period. This is borne out by Granger causality tests, reported in Table 1, which

Table 1: Granger causality tests for aggregate labor market variables

	2003q1-2019q4		2004q1-2016q2	
Model	VAR(4)	VAR(4) with trend	VAR(4)	VAR(4) with trend
Immigration				
Exclude hours	21.89***	18.97***	23.91***	23.87***
Exclude real native wage	6.234	4.654	11.48**	8.031*
Exclude both	25.86***	20.90***	33.23***	28.11***
Total hours				
Exclude immig.	3.230	1.342	3.161	1.773
Exclude real native wage	3.961	3.703	5.145	5.484
Exclude both	5.974	4.268	6.594	6.053
Real native wages				
Exclude immig.	12.95**	14.44***	11.15**	11.15**
Exclude hours	5.592	7.017	4.141	6.918
Exclude both	14.53*	16.26**	13.34	15.27*

Notes: The table reports, the Chi-squared values for the Granger causality tests from VARs of the year on year growth rates of the share of immigrants in the working population, the total number of hours worked and the average hourly native wage in the UK. The VARs use 4 lags and are run for the time periods, 2003(Q1)-2019(Q4) and 2004(Q1)-2016(Q2). ***,**, and * indicate significance at the 1%,5% and 10% level respectively.

show that immigration is Granger caused by the total number of hours worked and that native wages are Granger caused by immigration. These results are generated using a VAR of our three aggregate variables with 4 lags, both with and without a time trend, estimated on the entire sample and for the shorter sub-sample 2004(Q1)-2016(Q2), to demonstrate that the results are not due to Brexit or the sample's initial conditions. Interestingly total hours worked are not Granger caused by either native real wages or immigration in any specification or sample.

These results suggest that the level of immigration and native real wages are related to the total hours worked in the economy, which itself is surely affected by the macroeconomic environment and hence demand and supply effects. Empirical macroeconomics, as explained below in section 3, has developed methods to untangle individual effects from the multiple influences on a variable's time series. We apply these methods to identify the contribution of labor demand, supply and immigration shocks at both the aggregate and sectoral level, on immigration share, hours worked and native wages in the UK economy.

3 Structural model and identification

It is useful to think of the time series for the aggregate data as being generated by a three equation structural model, as in Baumeister and Hamilton (2019), where the three equations are a migration equation, a domestic labor supply equation and a domestic labor demand equation. These equations relate to different rows of the structural VAR we describe below.

A structural VAR, has the form

$$Sy_t = \kappa + bx_{t-1} + u_t$$

where y_t is a vector of endogenous variables and where x_{t-1} is a matrix containing p lagged values of y_t. In our case there are three endogenous variables: the year-on-year difference of the logs of, the economy-wide migration share, M_t^{agg}, the economy-wide total hours worked, H_t^{agg} and the economy-wide real wages of native workers, W_t^{agg}. Hence $y_t = (M_t^{\text{agg}}, H_t^{\text{agg}}, W_t^{\text{agg}})'$ and so the structural VAR for the aggregate variables can be written,

$$\underbrace{\begin{bmatrix} 1 & -\alpha_{MH} & -\alpha_{MW} \\ -\alpha_{HM} & 1 & -\alpha_{HW} \\ -\alpha_{WM} & -\alpha_{WH} & 1 \end{bmatrix}}_{S} \underbrace{\begin{bmatrix} M_t^{\text{agg}} \\ H_t^{\text{agg}} \\ W_t^{\text{agg}} \end{bmatrix}}_{y_t} = \underbrace{\begin{bmatrix} \kappa^M \\ \kappa^H \\ \kappa^W \end{bmatrix}}_{\kappa} + \underbrace{bx_{t-1}}_{(3\times 3p)(3p\times 1)} + \underbrace{\begin{bmatrix} u_t^M \\ u_t^P \\ u_t^D \end{bmatrix}}_{u_t} \tag{1}$$

where u_t^M, u_t^P and u_t^D are respectively the exogenous migration, aggregate productivity and aggregate labor demand shocks.

The first row of equation (1) describes the migration equation. Writing this out gives

$$M_t^{\text{agg}} = \kappa^M + \alpha_{MH} H_t^{\text{agg}} + \alpha_{MW} W_t^{\text{agg}} + \beta x_{t-1} + u_t^M$$

This is interpreted as an exogenous migration process subject to an exogenous aggregate migration shock, u_t^M, but which is also influenced by domestic demand and supply shocks via their effects on wages and hours. Thus aggregate migration is modeled as being subject to all three aggregate shocks; u_t^M directly and u_t^P and u_t^D indirectly via the other two equations. To identify the VAR we assume that the exogenous aggregate migration shock, u_t^M, only affects the migration share on impact. This implies that $\alpha_{HM} = \alpha_{WM} = 0$ in the S matrix.

The second and third rows of equation (1) describe the domestic labor supply and demand equations. These are identified via sign restrictions on their impulse response functions and so are best described using the reduced form VAR which is created by multiplying both sides of the structural VAR by the S^{-1} matrix.

$$\underbrace{\begin{bmatrix} M_t^{\text{agg}} \\ H_t^{\text{agg}} \\ W_t^{\text{agg}} \end{bmatrix}}_{y_t} = \underbrace{\begin{bmatrix} c^M \\ c^H \\ c^W \end{bmatrix}}_{S^{-1}\kappa} + \underbrace{S^{-1}bx_{t-1}}_{(3\times 3)(3\times 3p)(3p\times 1)} + \underbrace{\begin{bmatrix} + & \text{none} & \text{none} \\ 0 & + & + \\ 0 & - & + \end{bmatrix}}_{S^{-1}} \underbrace{\begin{bmatrix} u_t^M \\ u_t^P \\ u_t^D \end{bmatrix}}_{u_t} \tag{2}$$

The sign restrictions we impose are commonly used in the macroeconmics literaure. These are that supply shocks move price and quantity (wages and hours) in opposite directions whereas demand shocks move them in the same direction. Hence we assume in the second column of S^{-1} that u_t^P increases aggregate wages while decreasing aggregate hours. We regard this as an aggregate labor productivity or labor supply shock. In the third column we assume that a positive shock to u_t^D affects aggregate wages and aggregate hours positively, which we regard as an aggregate labor demand shock.

The sign restrictions imply restrictions on combinations of elements of the S matrix so that, for example, the sign restriction that the response of hours worked to the labor demand shock is positive implies that $\frac{-\alpha_{HW}}{\det(S)}$ is positive. In addition we also impose that α_{MH} in the migration equation of equation(1), as on aggregate it would be strange if increased migration is associated with lower hours worked. This logic does not apply at the sectoral level. We also impose that α_{hw} is positive in the second row of equation (1). This is the labor supply equation and so the supply of more hours worked is associated with higher wages. Similarly we impose that α_{wh} negative in the third row of equation (1). This is the labor demand equation and so higher wages are associated with lower hours demanded. Note we do not impose any restriction on α_{MW} a key parameter of interest and employ a diffuse prior for this parameter. Given these identification assumptions the contribution of each of these equations to the time series of each variable in the VAR is then determined by the data.

The imposed sign restrictions are intuitive and are consistent with the literature and standard economic theory. Their plausibility is further reinforced by the resultant historical decompositions of the aggregate time series, described in section 4 below. However, clearly, there are other ways to decompose the data. In section 5 below we discuss the robustness of the result to different identification schemes, including different Cholesky orderings and to identification using the penalty function approach. The Cholesky case is of interest as it is acknowledged to be a good way of summarizing the dynamic correlations in the data, see e.g. Sims (2003) and Baumeister and Hamilton (2024). Section 5 shows that the negative dynamic correlation between aggregate migration share and native wages is consistently present across a variety of approaches.

3.1 Estimated VAR

The estimated VAR also includes the sectoral variables, the sectoral migration share, m_t^{sec}, total hours worked in the sector, h_t^{sec}, and sectoral real wages of natives, w_t^{sec}. Thus the dependent variable of the VAR is six-dimensional, $y_t = (M_t^{\text{agg}}, H_t^{\text{agg}}, W_t^{\text{agg}}, m_t^{\text{sec}}, h_,^{\text{sec}} w_t^{\text{sec}})'$, and the reduced form can be written,

$$\underbrace{\begin{bmatrix} M_t^{\text{agg}} \\ H_t^{\text{agg}} \\ W_t^{\text{agg}} \\ m_t^{\text{sec}} \\ h_t^{\text{sec}} \\ w_t^{\text{sec}} \end{bmatrix}}_{y_t} = \underbrace{\begin{bmatrix} c^M \\ c^H \\ c^W \\ c^m \\ c^h \\ c^w \end{bmatrix}}_{S^{-1}\kappa} + \underbrace{S^{-1}bx_{t-1}}_{(6\times 6)(6\times 6p)(6p\times 1)} + \underbrace{\begin{bmatrix} + & \text{none} & \text{none} & \text{none} & \text{none} & \text{none} \\ 0 & + & + & \text{none} & \text{none} & \text{none} \\ 0 & - & + & \text{none} & \text{none} & \text{none} \\ \text{none} & \text{none} & \text{none} & + & \text{none} & \text{none} \\ \text{none} & \text{none} & \text{none} & \text{none} & + & + \\ \text{none} & \text{none} & \text{none} & \text{none} & - & + \end{bmatrix}}_{S^{-1}} \underbrace{\begin{bmatrix} u_t^M \\ u_t^P \\ u_t^D \\ u_t^m \\ u_t^p \\ u_t^d \end{bmatrix}}_{\epsilon_t} \tag{3}$$

We do not impose the same sign restrictions on the parameters of the S matrix at the sectoral level as we do at the aggregate level as shown in equation (3). A sectoral level migration shock may be the response from migrants already working in other sectors and so zero restrictions on sectoral hours and wages seems less appropriate. Similarly at the aggregate level it is intuitive that an increase in aggregate immigration should increase aggregate hours and so that α_{MH} is positive. However this need not be the case for every sector. As we have shown in Figure 1a above, in some sectors increased immigration may be associated with reduced total hours as migrant labor offsets an outflow of domestic labor. Thus we restrict the sectoral migration shock, u_t^m to simply be an increase in the sectoral migrant share in equation (3). The responses of sectoral migration shock will therefore not be clearly distinguished from the sectoral supply and demand shocks in every sector. Therefore we focus most of our analysis on the effects of the aggregate equations. However the analysis can nevertheless demonstrate the importance of sectoral shocks in total. That part of the evolution of the time series not explained by the identified aggregate equations must therefore be explained by the sectoral equations. As we show below this can be substantial in some sectors.

In our estimated model, for each sector we choose lag length, $p = 4$, for quarterly data, and we estimate the model following Baumeister and Hamilton's (2015) methodology quite closely. They show how beliefs about the signs of individual parameters of the S matrix and combinations of elements of the S matrix, such as those described above, can be incorporated into the priors of a Bayesian estimation procedure. They derive a Metropolis-Hastings algorithm for drawing from the posterior distribution for the parameters resulting from these priors. We use the programs supplied in Baumeister and Hamilton (2019) to estimate the model.[11] We also impose additional assumptions in the prior for the B parameters, that impose stationarity and set the prior to be very tight around zero for the parameters associated with the lagged sectoral variables in the aggregate variable equations, following e.g. Blake and Mumtaz (2017). This implies, as we will see below, that the dynamics of the aggregate variables are almost entirely determined by the 3×3 sub-VAR of the aggregate variables.

[11] We make 8,000,000 draws from the posterior for each sector discarding 6,400,000 draws as 'burn in' and retain every 400th draw as the 'thinning' process. We set $\lambda_0 = 100$, $\lambda_1 = 1$, $\lambda_2 = 1$ and $\lambda_3 = 100$ in the Minnesota prior, use the identity matrix for the covariance of the proposal distribution and adjust the jump size during the burn-in phase when it deviates too far from an acceptance rate of 0.35.

As a comparator, we also estimate the responses of the VAR using the Cholesky factorization. This is described below in the robustness section, section 5, below. For this case we impose the same restrictions on the B parameters, and assume that the prior and posterior for B and Σ belong to the Normal–Wishart family, which allows one to sample directly from the posterior, following Uhlig (2005).[12]

3.2 The structural model: historical decompositions and counterfactuals

Each estimated draw of the S matrix allows the construction of a time series of fundamental shocks, u_t, from the estimated reduced form errors, ϵ, via the formula, $\epsilon_t = S^{-1}u_t$. The observed time series can then be reconstructed using these time series of fundamental shocks by recursive iteration of the estimated VAR equation as described in Hamilton (1994) and briefly in Appendix A.1. This is the historical decomposition. Our 'counterfactual analysis' is then the historical decomposition with the contribution of one of the structural equations set to zero. One aspect that is not typical in our counterfactual is the accounting of the contribution of the specified structural constant term to the steady state growth rate of each variable. This is important and has hitherto been ignored by the literature.

The counterfactual reduced form error, ϵ_t^{CF}, where one of the fundamental shocks is set to zero, is simply $\epsilon_t^{CF} = S^{-1}u_t^{CF}$ where u_t^{CF} is u_t with one element set to zero e.g. the second element of u_t is set to zero for all t, if the influence of second fundamental shock on the observed time series is being removed.

The structural constant terms κ can be constructed in the same way by multiplying the estimated reduced form constant by S. The counterfactual constant term, κ^{CF} will then be κ with the element corresponding to the shock replaced by zero. The counterfactual reduced form constant term is then given by the vector $S^{-1}\kappa^{CF}$. As we have emphasized above this 'counterfactual' should not be interpreted as performing a 'pseudo experiment'. Rather, this counterfactual is simply a different presentation of the standard historical decomposition to quantify the contribution of a specific structural equation over the sample period.

4 Results

In this section we first discuss the results for aggregate variables, we do this initially via the impulse response functions. These are the building blocks for the discussion of the historical decompositions which will be the focus of our attention. A key motivation for this paper is the idea that different contemporaneous shocks may offset each other and the historical decompositions show if and when offsetting effects occur in each outcome variable. We also use the historical decompositions to quantify the contribution of each identified aggregate shock to each outcome variable using the 'counterfactual analysis' described above in section 3.2.

[12] We make 100,000 draws from the posterior for each sector discarding 50,000 draws as 'burn in' and retain every 25th draw as the 'thinning' process.

In section 4.3 we discuss the effects of the aggregate shocks at the sectoral level. We first discuss the sectoral impulse responses to the aggregate shocks and sectoral level 'counterfactual analysis' to demonstrate the differential effects of aggregate shocks across sectors. We also described the responses of sectoral variables to sectoral shocks, although with the caveat that these shocks are less well identified as discussed in section 3.1.

4.1 Results for aggregate shocks on aggregate variables

4.1.1 Impulse response functions of aggregate shocks

The impulse response functions map out the dynamic paths of all variables in the VAR in response to a one standard deviation innovation for each of the identified shocks.[13] This is done for each draw from the posterior distribution of the parameters which therefore produces a distribution of impulse responses. In Figure 3 we plot a subset of responses: the responses of aggregate variables to aggregate shocks. Figure 3 plots the 16th, 50th and 84th quantiles from the posterior from one sector, the unskilled transport services sector, and shades the 16-84th quantile confidence set.[14] We have colored the responses to each shock differently so that when we use the same colors for each shock in the historical decompositions in Figure 4, the contribution of each shock is clear.

The first identified shock in Figure 3, colored green, is the exogenous aggregate migration shock described in section 3. As one would expect this leads to a strong and persistent positive response of the aggregate migration share, with the response remaining positive for about two years. This shock is not associated with increased hours worked. The positive association of migration share and hours is instead present in the labor demand shock discussed below. The response of wage growth to the migration shock is negative for over a year after impact. Note this is not due to the imposed sign restriction in equations (1) and equations (2), where $\alpha_{MW}$is not restricted. Also, as discussed in section 5, this negative association is present across different identification schemes including those with no zero restrictions on the migration shocks. The second identified shock, colored yellow, is the labor supply shock which we interpret as a labor productivity shock, where there is a negative correlation between wage growth and hours. Interestingly the positive productivity shock which increases wages and reduces hours is associated with increased migration share.

The third identified shock in Figure 3, colored blue, is the aggregate labor demand shock described in section 3. These impulses are intuitive with hours growth and wage growth rising persistently for over a year. The growth in immigration share rises in response to this shock before declining when the growth of hours subsides. This shock accounts for almost all of the positive correlation between immigration and hours growth on impact. The interpretation of this shock as a business cycle/demand shock is reinforced by the historical decompositions in Figure 4 below, which show that this shock explains most of the variation in hours over the sample period.

[13] See the Appendix A.1, or Hamilton (1994), for description of impulse responses.

[14] As Figure 7 show the aggregate responses from other sectors are almost identical.

Figure 3: Impulse responses of aggregate variables to aggregate shocks

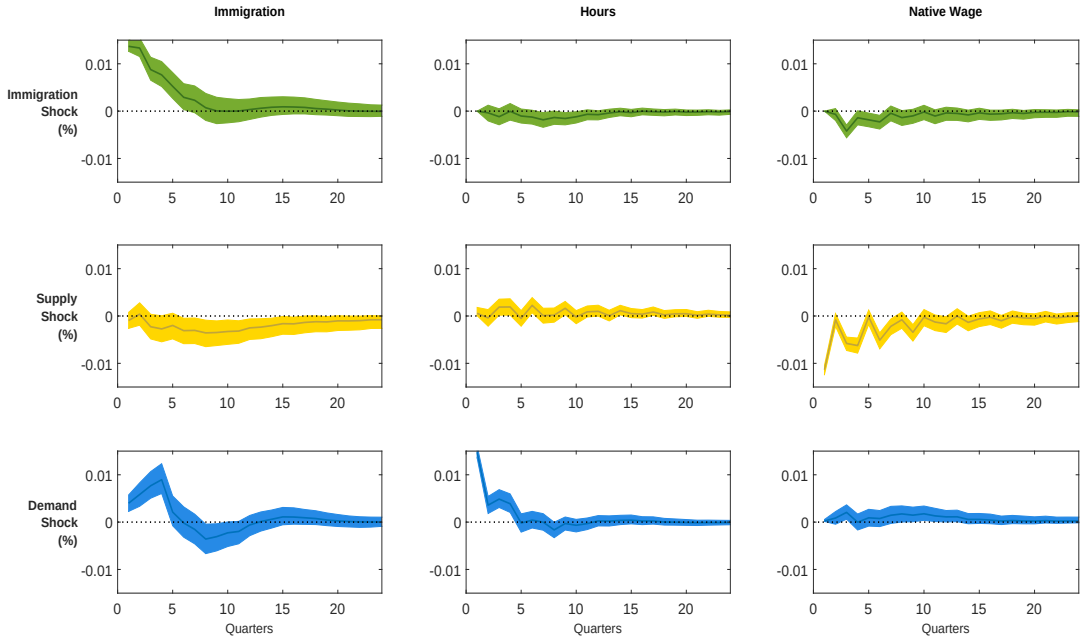
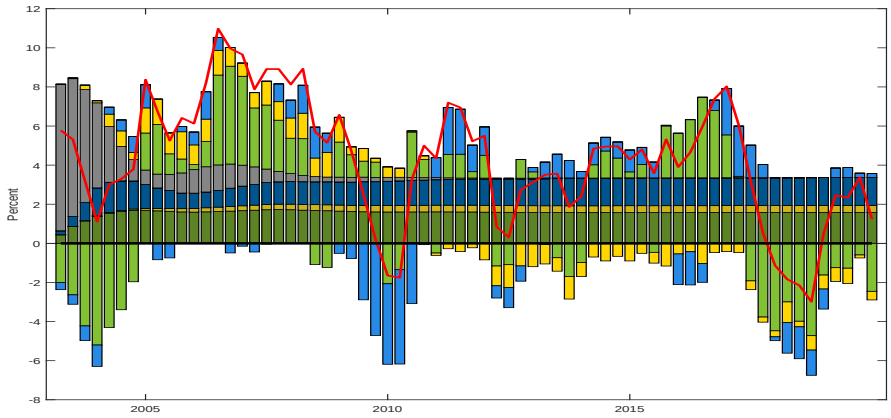


Figure 3 plots the impulse responses of the aggregate variables to aggregate shocks. The impulses of the exogenous migration shock are colored green, those of the labor supply shock colored yellow and those of the labor demand shock colored blue. The shaded region is the area between the 16% and 84% quantiles of the posterior distribution with the median colored in a darker line.

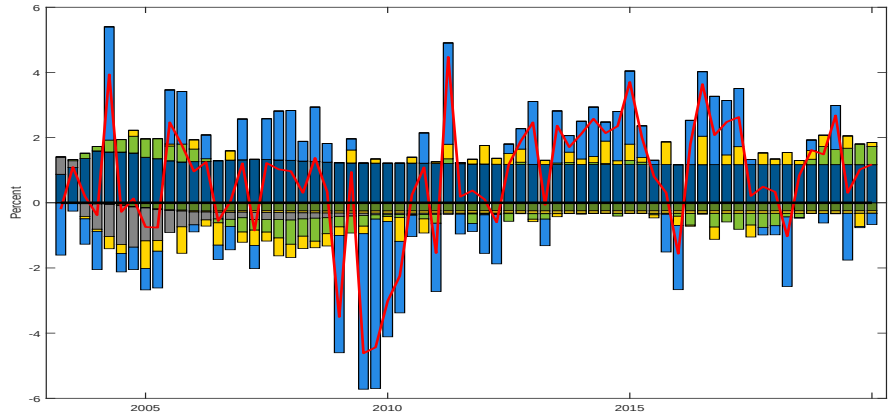
We asked at the outset whether immigration could be thought of as an exogenous shock. The impulses responses in Figure 3 suggest that aggregate immigration is influenced by shocks that could be considered aggregate supply, and aggregate demand. However the exogenous migration shock also has a strong migration response. Thus aggregate migration seems to be influenced by both supply and demand as well as its own dynamics.

Figure 4: Historical decomposition of aggregate variables - sign restriction approach

(a) Aggregate migration



(b) Aggregate hours



(c) Aggregate native wages

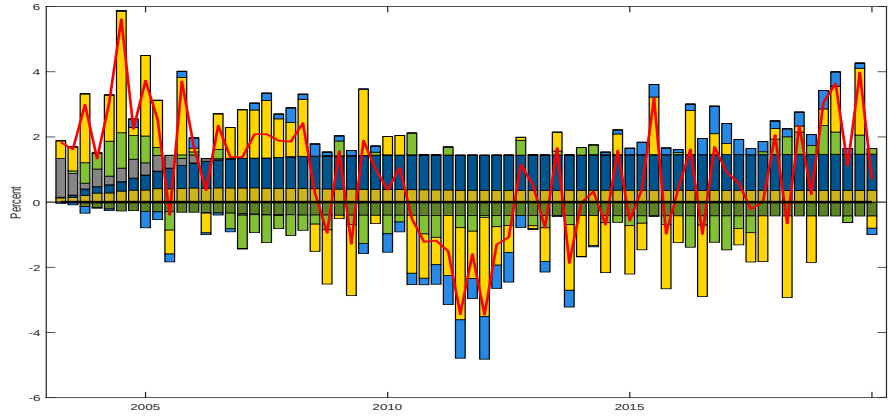


Figure 4 plots the median estimate of the historical contributions of the aggregate identified shocks, the initial conditions and the structural constant terms, to aggregate native migration share growth in Panel (a), to aggregate hours growth in Panel (b), and to aggregate native wage growth in Panel (c). In each panel the red line plots data for data series. The colors of the bars relate to the colors of the impulses in Figure 3 for both the constant and error terms. The contribution of the initial conditions is colored grey.

4.1.2 Historical decomposition of aggregate variables

Given the estimated parameters, the observed data for each time series used in the VAR can be decomposed into the contributions from each fundamental shock by iterating on the estimated VAR.[15] The contribution of each shock is highly related to its impulse response function, as described in e.g. Hamilton (1994). Figure 4 displays the historical decompositions of the aggregate variables in terms of aggregate shocks. Note that we also decompose the reduced form constant terms into their structural components as described in section 3. The contribution of the constant terms will be very important for our counterfactual analysis.

The historical decompositions in Figure 4 are shown as a stacked bar chart, using the median responses. The observed year-on-year percentage growth for each time series is plotted as a red line. The sum of the stacked historical decompositions, in each time period, match each observed data series very well.[16] In each panel of Figure 4 we have colored the contribution of the shock to match those of the impulse responses in Figure 3. Thus the contribution of the aggregate labor demand shock is colored blue, the aggregate labor supply shock is colored yellow and the aggregate migration shock is colored green. The structural constant terms are colored in the same way although in a slightly darker shade to more easily distinguish them. The contribution of the initial conditions is colored gray.

Panel a) of Figure 4 shows the historical decomposition for the aggregate migration series. This shows that the constant terms from the aggregate migration and aggregate labor demand structural equations make a significant positive contribution to the evolution of the immigration share. The structural constants are proportional to the steady state growth rates in each structural equation. Hence Figure 4 indicates that the steady state growth rate of exogenous migration is negatively associated with the steady state rate of growth of native wages. The shocks to these two equations are also the dominant factors in the variation of the aggregate migration series. Aggregate migration shocks are the most important determinant, with a noticeably large negative shock after the Brexit referendum. However there is also an important role played by aggregate labor demand shocks, particularly after the financial crisis of 2008.

Panel b) of Figure 4 shows the historical decomposition for the aggregate hours worked series. This shows a significant role played by the structural constant from the labor demand equation. Thus steady state hours growth is mostly determined by the steady state growth rate of labor demand. The labor demand shock also plays a dominant role in the variation of the series. This is consistent with the Granger casuality results presented in Table 1 which showed that aggregate hours Granger caused the other data series but the other series did not Granger cause aggregate hours. The historical decomposition has a very intuitive pattern, being very negative after the 2008 financial crisis and then gradually more positive afterwards. The other shocks are present but have only relatively small contributions.

[15] This is briefly described in the Appendix A.1, where the historical decomposition formula is given by equation (A3).

[16] The sum of the median contributions do not necessarily sum to the original, see Bergholt, et al (2024), but as Figure 4 shows the match is quite close.

Panel c) of Figure 4 shows the historical decomposition for aggregate native wages series. This shows that the constant term is the product of offsetting positive and negative forces. The aggregate labor demand and labor supply equations have positive influence but the aggregate migration equation has a negative influence. For the variation, the demand shock plays an important role in the period following the financial crisis of 2008, but otherwise the labor supply shock is the dominant force. It has a positive, contribution at the end and beginning of the sample period and a noticeably negative role around the time of the Brexit referendum.

4.1.3 How large are the effects of aggregate shocks? - a counterfactual analysis

We quantify the effects of the structural equations on the evolution of each observed data series using the counterfactual anaylsis described in section 3.1. This sets the contribution of each structural equation to zero, one at a time, and then recalculates each time series as per a historical decomposition as described in section 3.2. The difference between this counterfactual time series and the observed time series highlights the contribution of the left-out structural equation to the observed time series.

Figure 5 plots the counterfactual time series for aggregate native wages with the migration equation's constant and error terms set to zero. The median and the 16% and 84% quantile bands of the counterfactual are colored green and the actual time series is colored red. The green band is generally above the actual series, which shows that aggregate native wage growth is positively impacted by the absence of the migration equation i.e. over the sample period the exogenous aggregate migration process is associated with lower wage growth. Figure 5 is consistent with the historical decomposition displayed in Figure 4. The time periods before the financial crisis and in the period before Brexit were those with the strongest negative effects of the migration shock on native wages in both Figures. The total contribution of the migration equation is strongly influenced by the constant term. This is present in every period and its effect compounds so that the median counterfactual is above the data series in almost every period. We quantify this effect across sectors in Table 2 below in section 4.2.

Figure 5: Counterfactual for aggregate native wage growth with the migration equation set to zero

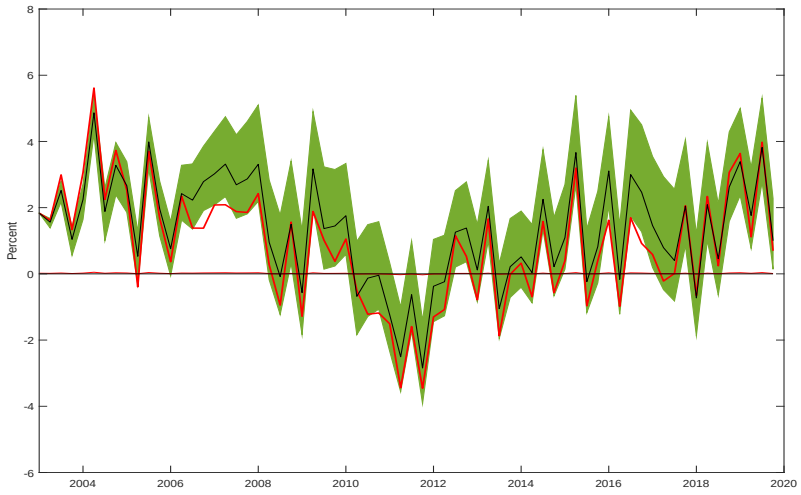
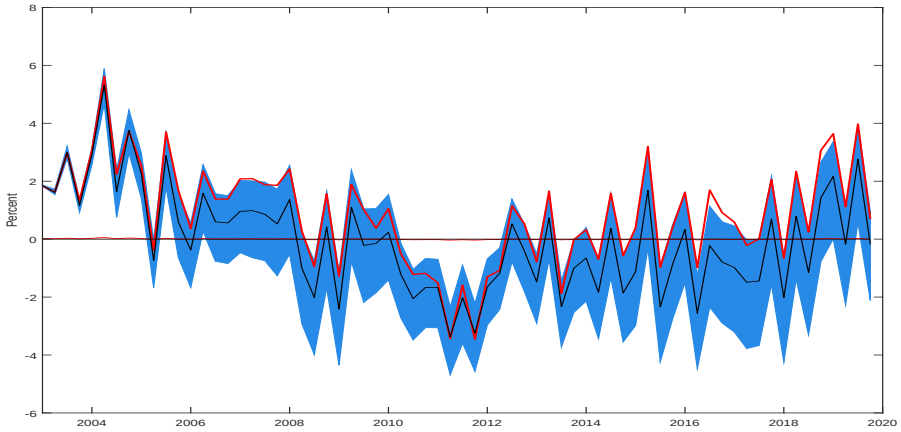


Figure 5 plots the counterfactual time series for native wage growth with the immigration equation set to zero. The red line plots the observed data series for aggregate wage growth and the shaded region shows the area between the 16% and 84% quantiles of the counterfactual posterior distribution with the median plotted in black. This counterfactual distribution is mostly above the data over the sample period, illustrating that the absence of the migration equation implies a higher rate of native wage growth in the counterfactual.

Figure 6 plots the equivalent counterfactual time series with a) the demand equation and b) the supply equation set to zero. The demand equation has a persistently positive effect on native wage growth in contrast to the exogenous migration equation, while the supply equation has initially a positive effect on native wages growth but then a negative effect during the recession following the 2008 financial crisis and a roughly neutral effect thereafter. Thus the supply equation has significant effects on wages but these all roughly cancel out over sample period, consistent with the historical decompositions in Figure 4.

Figure 6: Counterfactuals for aggregate native wage growth

(a) Counterfactual with the demand equation set to zero



(b) Counterfactual with the supply equation set to zero

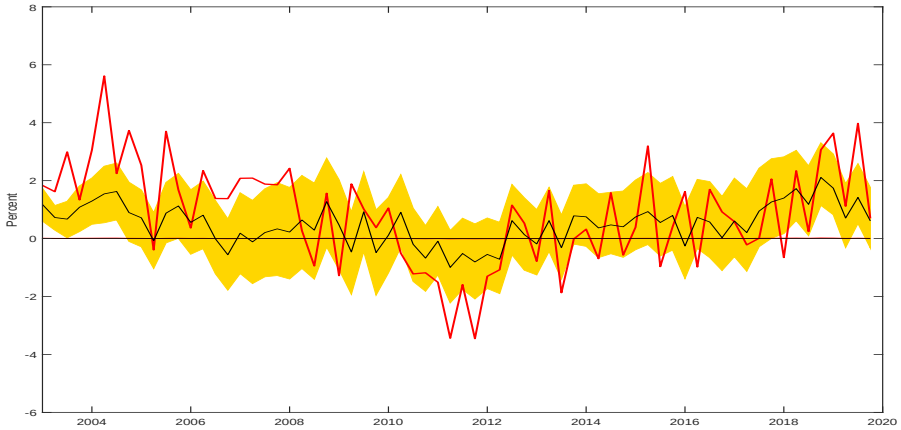


Figure 6 plots the counterfactual time series for native wage growth where in panel a) the demand equation and in panel b) the supply equation, are set to zero. The red line plots the data series for aggregate native wage growth and the shaded region is the area between the 16% and 84% quantiles of the counterfactual posterior distribution with the median plotted in black. The distribution for the absence of the demand equation is mostly below the data over the sample period, illustrating that the absence of the demand equation implies a lower rate of native wage growth in the counterfactual. The colors of the plots relate to the colors of the impulses in Figure 3.

Figure 7: Impulse responses for the unskilled manual sectors using the sign restriction approach

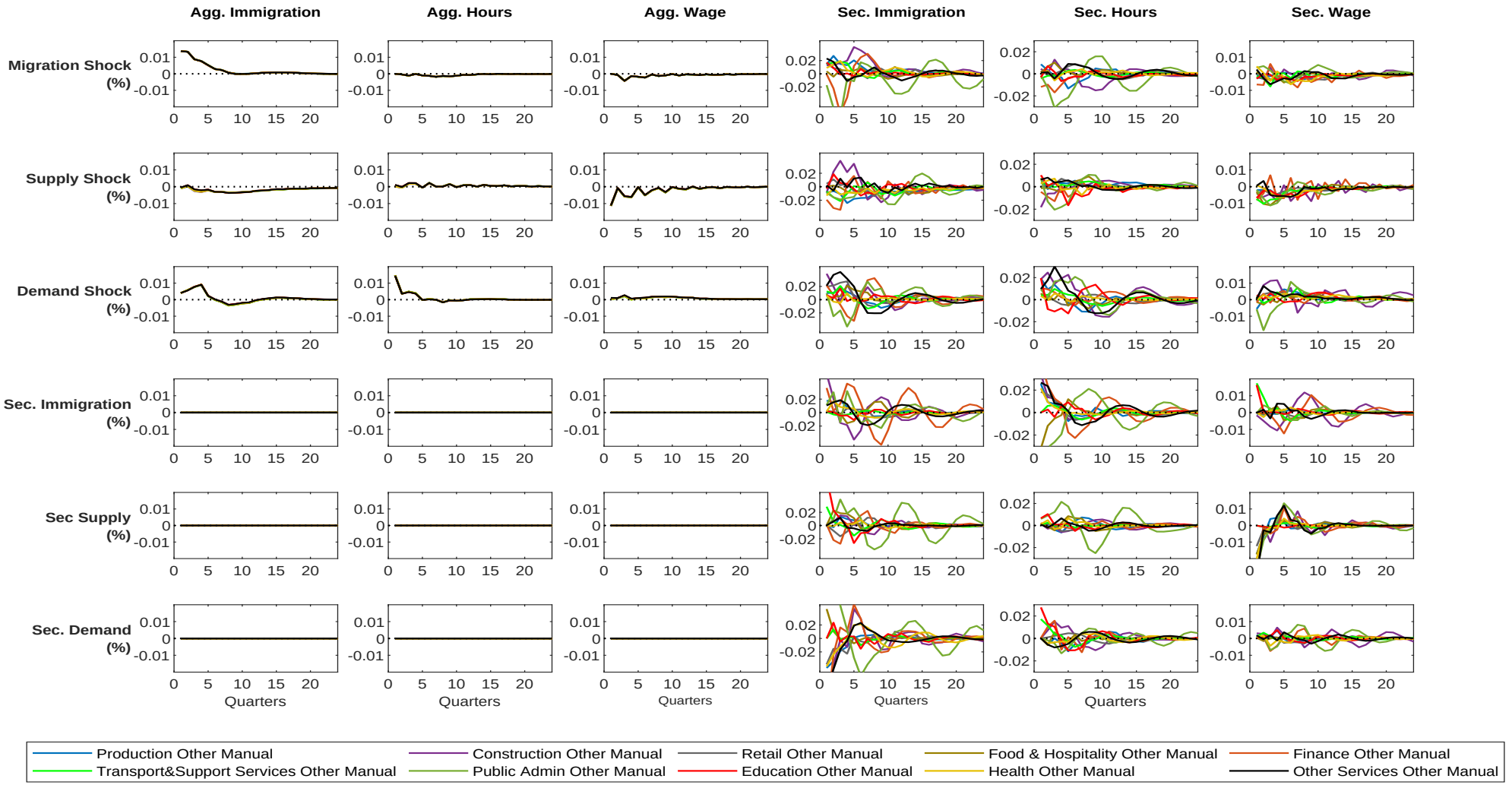


Figure 7 plots the median impulse responses for the unskilled manual sectors using the sign restrictions described in section 3. Each row plots the responses to a particular shock (row 1 is the aggregate migration shock, row 2 is the aggregate supply shock, etc.) and each column is the responses of a particular variable (column 1 is aggregate migration, column 2 is aggregate hours, etc.). The responses of all 10 sectors are plotted together. By construction, the sectoral variables play very little role in aggregate dynamics and so the aggregate responses are all very similar to each other and appear for the most part to be a thick line.

4.2 Effects of aggregate shocks on sectoral variables

In this section we discuss the sectoral variation in the effects of the aggregate shocks. We start by discussing the variation in the sectoral impulse responses to the aggregate shocks and then discuss how these translate into different counterfactuals across sectors

Figure 7 plots the median impulse responses from the 10 VARs estimated for the 10 unskilled manual sectors in the dataset.[17] Note that these figures plot the median impulse responses for all 10 sectors and yet the impulse responses of the aggregate variables to aggregate shocks appear for the most part to be one thick line. As the VARs for each sector are run independently this similarity also demonstrates the accuracy of the estimation process. The restrictions, described in section 3.1, that sectoral variables play very little role in determining aggregate variables are evident in the negligible responses of aggregate variables to the sectoral shocks displayed in the lower left 3×3 submatrices of Figure 7. Thus the top left 3×3 submatrix of Figure 7 is close to the responses of an independent 3 dimensional VAR in the aggregate variables. These responses were section discussed in section 4.1.1.

The top right 3×3 submatrix of Figure 7 shows the responses of the sectoral variables to the same aggregate shocks. These submatrices show the different reactions across sectors to aggregate shocks both in terms of scale but also sign with, for example, some sectors experiencing an increase in sectoral migration share in response to an aggregate migration shock and others a decrease. This demonstrates the heterogeneity of the response to aggregate migration across sectors which consequently suggests differences in the importance of sectoral shocks which we discuss below. Nevertheless there are also similarities across sectors. For example the responses of sectoral native wages and hours in the third row are positive in the short run in almost every sector. This reinforces our interpretation of the third shock as an aggregate demand or business cycle shock.[18]

We quantify the difference effects of aggregate shocks across sectors using the same counterfactual analysis described in section 4.1.3 above. Table 2 reports the counterfactual native wage growth where the effects of one of the three aggregate equations is set to zero, for all 35 sectors along over the sample period. Table 3 reports the same for migration share.

The first column of Table 2 displays the cumulative growth of median real native wages over the sample period. This shows that real native wage growth was very small in many sectors. The 2010-2019 decade was notable as being a period of pay restraint, associated with 'austerity' policy regime following the financial crisis. In many professional sectors native real wage growth was negative with education and media professional sectors showing the largest declines. In the unskilled manual sectors by contrast, most sectors experienced positive native wage growth of between 10% and 20% over the sample period.[19]

[17] The impulse responses for the other sectors are available on request and those for the Cholesky approach are displayed in Appendix B.

[18] The exception being the 'Public Administration Other Manual' sector which as Figure 1a showed to be an outlier with a large drop in native labor employed over the sample period. Our policy has been to not exclude outliers, or treat one sector differently from another. The VARs are run independently of each other with the same specification.

[19] The sample period is notable for being a period of sluggish real wage growth and this pattern is

The second column of Table 2 displays the counterfactual growth of native real wages where the migration equation is set to zero. We highlight in bold notable sectors with large differences between the counterfactual time series for native wage growth and the observed time series. The unskilled manual group has many sectors with large differences, such as food and hospitality, retail and finance. In almost all unskilled manual sectors, the counterfactual native wage was higher than the observed native wage, with the sole marginal exception being the public administration sector. For the professional grouping, in contrast, native wage growth is significantly lower in the counterfactual in the scientific and other services sectors. This is consistent with immigrant labor in these sectors being complementary to domestic labor. Four professional sectors show large positive differences. These are the construction,public administration, retail and transport professional sectors. This is consistent with immigrant labor in these sectors being a substitute for domestic labor.

The third column of Table 2 displays the counterfactual growth of native real wages with the demand equation set to zero. The patterns in this column generally go in the opposite direction to those in column two. This illustrates the countervailing forces acting on native wages. Again there is significant heterogeneity across sectors. Noticeably, native wages in the transport sectors at all skill levels appear to be particularly sensitive to demand. The counterfactuals for the absence of supply equation are listed in the fourth column. These are weaker effects than the other two which is consistent with Figure 6b since, as we have seen, the effects of the supply equation cancel out over time.

Table 3 repeats the exercise in Table 2 but for the migration share series. Column one confirms the findings of Figure 1a that the migration share grew across all sectors over the sample period, although with substantial heterogeneity across sectors. When the migration equation is set to zero, aggregate immigration, the final row of Table 3, is much muted but still positive due to the influence of the demand and supply. The scale of the reduction in migration share varies a lot across sectors. Indeed in the public administration sector, the migrant share grows when the aggregate migration equation is set to zero. While this result may be considered an outlier, it should also be noted that this is a sector which experienced a large decline in native employment over the sample period following the 'austerity' policy regime. Columns three and four show that the absence of demand and supply reduces growth in the migrant share with, as before, substantial heterogeneity across sectors.

found in other official data series such as the ONS monthly wages and salaries survey, available at https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes /bulletins/averageweeklyearningsingreatbritain/january2025.

Table 2

Cumulative native wage growth 2003-2019 by sector in the data and under counterfactuals setting structural equations to zero.

Sector	Native wage growth in data	Counterfactual Migration	Counterfactual Demand	Counterfactual Supply
Professional sectors				
Production	0.99	0.98	0.85	0.96
Construction	1.05	**1.24**	0.91	0.98
Retail	0.98	**1.17**	0.96	0.96
Media&IT	0.93	1.06	0.70	0.92
Finance	0.98	1.00	0.73	0.93
Scientific	0.99	0.91	0.93	0.90
Transport&Support Services	1.05	**1.25**	0.83	1.00
Public Admin	1.00	**1.13**	0.75	0.98
Education	0.91	0.90	0.89	0.83
Health	1.05	1.07	1.00	0.96
OtherServices	1.08	0.95	0.99	0.99
Other non-manual sectors				
Production	1.11	1.16	1.13	1.10
Retail	1.04	1.09	0.92	1.00
Media&IT	1.03	1.00	0.97	0.99
Finance	1.21	**1.40**	1.24	1.20
Scientific	1.00	0.83	1.08	0.93
Transport&Support Services	1.13	**1.48**	0.94	1.12
Public Admin	1.08	1.12	1.08	1.06
Education	1.07	0.94	0.90	0.96
Health	1.06	1.08	0.85	1.02
OtherServices	1.11	**1.35**	0.91	1.05
Skilled manual sectors				
Production	1.10	**1.22**	**0.82**	1.07
Construction	1.11	**1.24**	**0.92**	1.03
Transport&Support Services	1.04	1.09	**0.78**	1.03
Public Admin	1.15	1.27	1.03	1.10
Unskilled manual sectors				
Production	1.13	1.27	0.88	1.11
Construction	1.13	1.21	0.78	1.04
Retail	1.22	**1.41**	0.86	1.22
Food&Hospitality	1.23	**1.36**	1.08	1.22
Finance	1.08	**1.35**	0.91	1.07
Transport&Support Services	1.14	1.25	0.91	1.09
Public Admin	1.19	1.17	1.37	1.11
Education	1.12	1.28	0.89	1.07
Health	1.13	1.30	0.89	1.12
OtherServices	1.18	**1.36**	0.89	1.15
Aggregate wage growth	1.15	1.25	0.97	1.11

Notes: The table reports the cumulative native wage growth 2003-2019 by sector in the data, and for the median in the counterfactual series, derived by setting one of the aggregate structural equations to zero. The cumulative native wage growth is calculated as $\prod_{t=1}^{T}(1 + \text{native wage growth}_t)^{0.25}$. Selected sectors with a noticeable difference in the native wage growth between the counterfactual and the observed time series are highlighted in bold.

Table 3

Cumulative migration growth 2003-2019 by sector in the data and under counterfactuals setting structural equations to zero.

Sector	Migration Share Growth in data	Counterfactual Migration	Counterfactual Demand	Counterfactual Supply
Professional Sectors				
Production	1.79	1.95	**0.69**	1.80
Construction	1.61	1.80	1.51	1.76
Retail	1.50	**1.20**	1.05	1.58
Media&IT	1.48	**0.84**	1.31	1.46
Finance	1.48	**1.07**	**1.72**	1.49
Scientific	1.60	**1.10**	1.48	1.54
Transport&Support Services	1.39	**1.18**	**0.89**	1.36
Public Admin	1.34	**2.54**	**0.75**	1.32
Education	1.45	1.42	2.12	1.52
Health	1.32	1.31	0.98	1.26
OtherServices	1.24	0.90	1.66	1.23
Other Non-Manual Sectors				
Production	1.81	**0.52**	**3.63**	1.61
Retail	1.70	1.65	2.35	1.80
Media&IT	1.27	1.11	1.37	1.19
Finance	1.79	1.60	1.70	1.68
Scientific	2.10	**1.45**	**1.34**	1.93
Transport&Support Services	1.39	1.23	**0.94**	1.26
Public Admin	1.03	**0.59**	1.10	0.93
Education	1.13	0.93	1.34	1.03
Health	1.47	**1.78**	1.42	1.48
OtherServices	1.41	1.43	1.08	1.49
Skilled Manual Sectors				
Production	2.27	2.63	**1.11**	2.27
Construction	2.14	**1.09**	**1.40**	1.74
Transport&Support Services	1.73	**1.27**	1.65	1.65
Public Admin	1.13	**0.56**	1.36	0.94
Unskilled Manual Sectors				
Production	2.83	**1.42**	1.99	2.60
Construction	2.28	**0.89**	1.38	2.55
Retail	2.45	**1.90**	**1.27**	2.45
Food&Hospitality	1.72	1.86	**0.68**	1.70
Finance	2.13	2.37	1.85	1.83
Transport&Support Services	2.72	**2.00**	1.85	2.41
Public Admin	1.63	**4.33**	**1.30**	1.59
Education	1.94	1.77	1.43	1.91
Health	2.45	1.76	1.71	2.31
OtherServices	1.53	1.268	**0.74**	1.48
Aggregate Migration Share Growth	2.03	1.55	1.94	1.60

Notes: The table reports the Cumulative migration growth 2003-2019 by sector in the data, and for the median in the counterfactual series, derived by setting one of the aggregate structural equations to zero. The cumulative migration share growth is calculated as $\prod_{t=1}^{T}(1 + \text{migration sharegrowth}_t)^{0.25}$. Selected sectors with a noticeable difference in the migration share growth between the counterfactual and the observed time series are highlighted in bold.

4.3 The importance of the sectoral level equations

We now focus on the extent of sectoral variation in the impact of the sectoral equations. The impulse responses to sectoral shocks are displayed in the bottom right 3×3 submatrix of Figure 7. One broad feature that immediately stands out is the heterogeneity across sectors. Rather than describe the responses of all 35 sectors, our approach is to look at the historical decompositions of the sectoral wage series in two contrasting example sectors, the unskilled manual retail sectror and unskilled manual construction sectors, which have both experienced large increases in immigration.

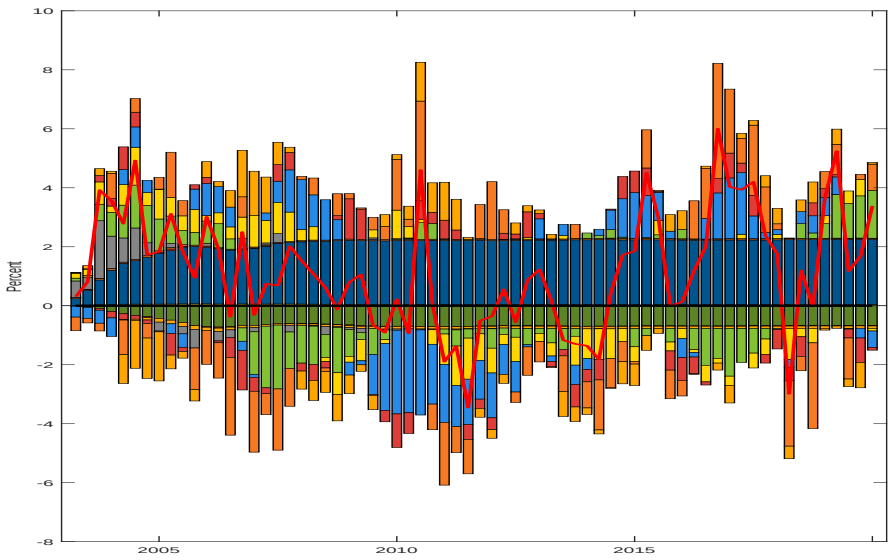
Historical decompositions at the sectoral level have thirteen different contributing factors; the three aggregate and the three sectoral shocks together with the six structural constants and initial conditions. As we stressed in Section 3 the individual sectoral shocks are not as tightly identified as their aggregate counterparts and so we focus our discussion here on the total extent of all the sectoral shocks. We have therefore colored the sectoral constants and shocks different shades of orange to visually demonstrate the importance of the sectoral variation in a particular sector, rather the importance of one particular shock. However for reference the sectoral migration is the reddest shade and sectoral demand the palest. As in Figure 4 we have also decomposed the constant effects into parts associated with their fundamental shocks. We have again used shades of orange for the sectoral constant terms, again to visual highlight the effect of the sectoral processes in total.

Figure 8a for the unskilled manual retail sector shows that aggregate shocks are most important for this sector. Wage growth is mostly determined by aggregate demand with an offsetting negative effect from aggregate migration. In terms of the timing of the shocks wages were negatively influenced by the financial crises and by aggregate migration in the period before the finacial crisis. The effects of sectoral shocks seems quite random. In contrast Figure 8b for the unskilled construction sector, shows that sectoral shocks have a large role in this sector. The shock labelled sectoral migration, although which might also be interpreted as sectoral supply, has a large negative effect on wage growth and in its variation, although aggregate demand also has an important role in wage growth inthis sector.

Taken together these figures illustrate how the contribution of aggregate and sectoral demand, supply and migration to native wage growth differs across sectors, and that in some sectors the importance of sectroal variation is considerable. We place the historical decompositions of sectoral wage growth for all 35 sectors in Appendix C where this is indicated by the extent of orange shades in each sector's figure.

Figure 8: Historical decomposition of native wages in unskilled manual retail and unskilled manual construction sectors

(a) Unskilled manual retail sector



(b) Unskilled manual construction sector

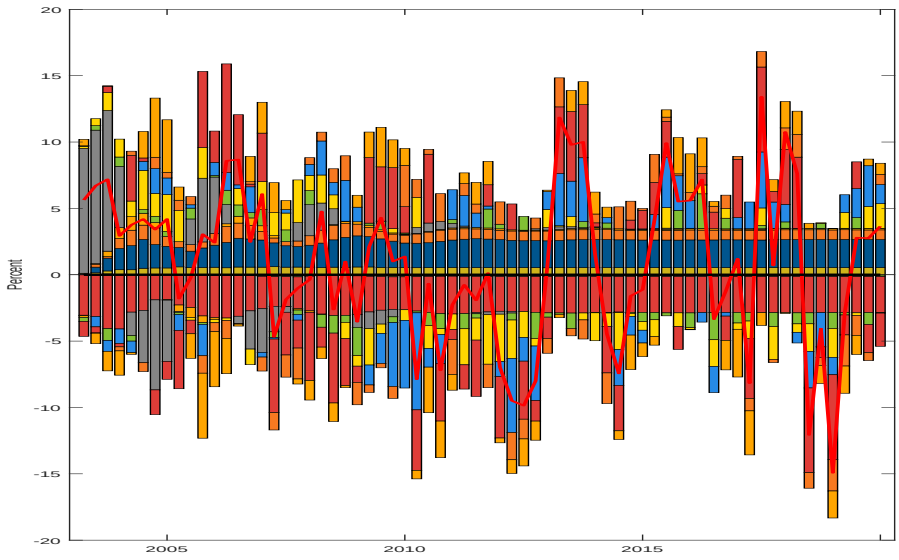


Figure 8 plots the median estimate of the historical contribution of each shock to native wage growth in the unskilled manual retail sector, Panel a), and in the unskilled manual construction sector, Panel b). In each panel the red line plots sectoral native wage growth. The colors of the bars for the aggregate shocks relate to the colors of the impulses in Figure 3 for both the constant and error terms. The colours of the sectoral shocks and constants are colored different shades of orange with sectoral migration the reddest and sectoral demand the palest.

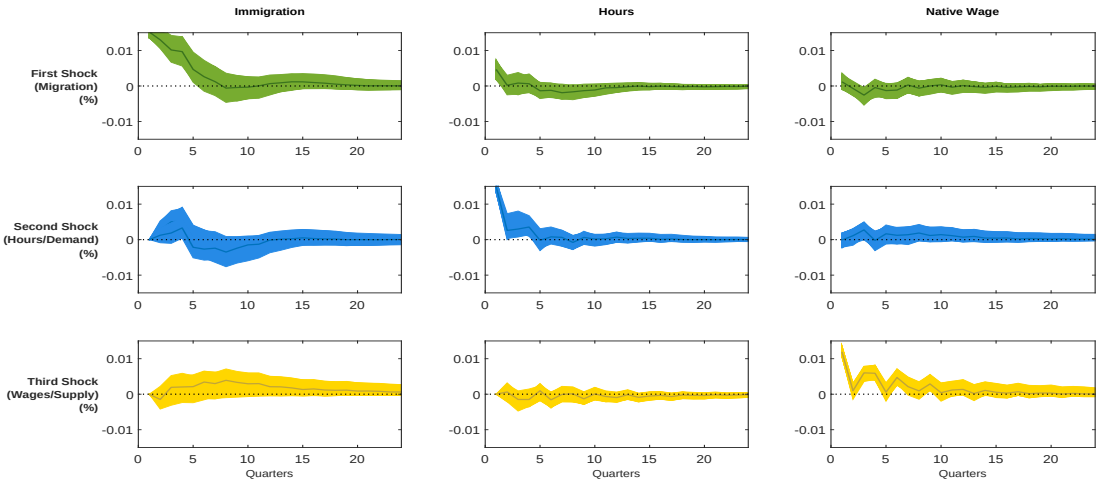
5 Robustness

In this section we present results from two Cholesky identifiifications (one where the migration series is ordered first and one where it is ordered last) and also using a penalty function approach, following Mountford and Uhlig (2009). Cholesky decompositions have long been regarded as a good way of describing the dynamic correlations in the data, see e.g. Sims (2003), Baumeister and Hamilton (2024). The penalty function identification does not use zero restrictions, other than for the orthogonality of the identified shocks, and identifies aggregate migration shocks as having positive effects on migration, aggregate demand shocks as having a positive effects on hours and wages and aggregate supply shocks as having a positive effect on hours and a negative effect on wages.

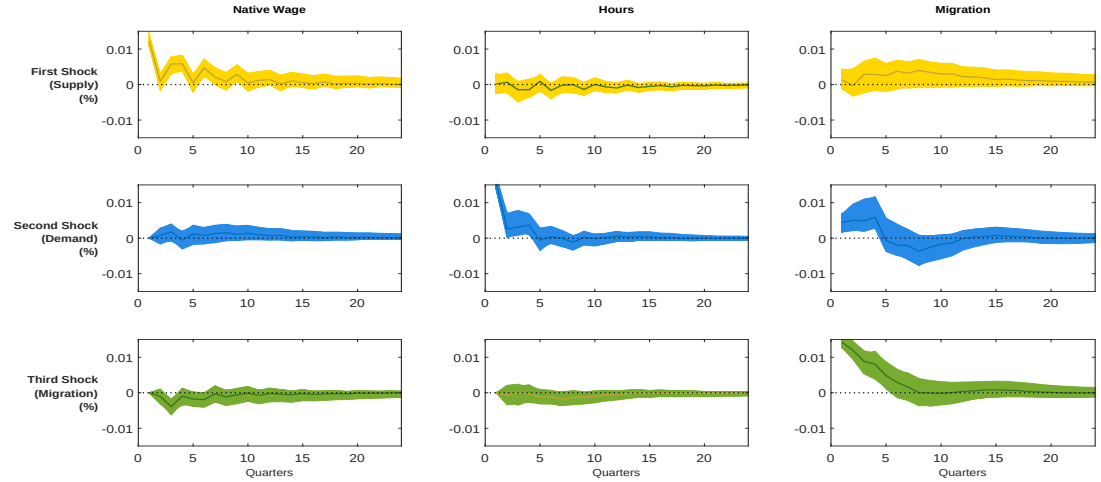
Figure 9 plots the impulse responses from these three alternative identification schemes. It shows that the impulses are quite similar to each other. We have illustrated this by coloring the responses with the same colors as the corresponding shocks in Figure 3. Thus the differing zero restrictions imposed across the different identification schemes do not dominate the underlying dynamic correlations in the data. Figure 10 plots the historical decompositions from the second Cholesky ordering where migration is ordered last. These historical decompositions are very similar indeed to those in Figure 4 above. The negative effect of the Brexit referendum on migration is clearly assigned to the migration process and the negative demand effect on migration is also apparant as they are in Figure 4. Aggregate supply effects play a larger role in determining wages but the overall narrative is the same. The results for the other two identification approaches, presented in Figures B1 and B2 in the appendix, are also similar, although aggregate migration shocks determining almost all of the evolution of migration share in these case, but it is still the case that wage growth is affected by multiple offsetting forces, with positive demand and supply effect offset by negative migration effects.

Figure 9: Impulse responses from alternative identification methods

(a) Impulse responses from Cholesky identification



(b) Impulse responses from Cholesky identification with reversed ordering



(c) Impulse responses from penalty function identification

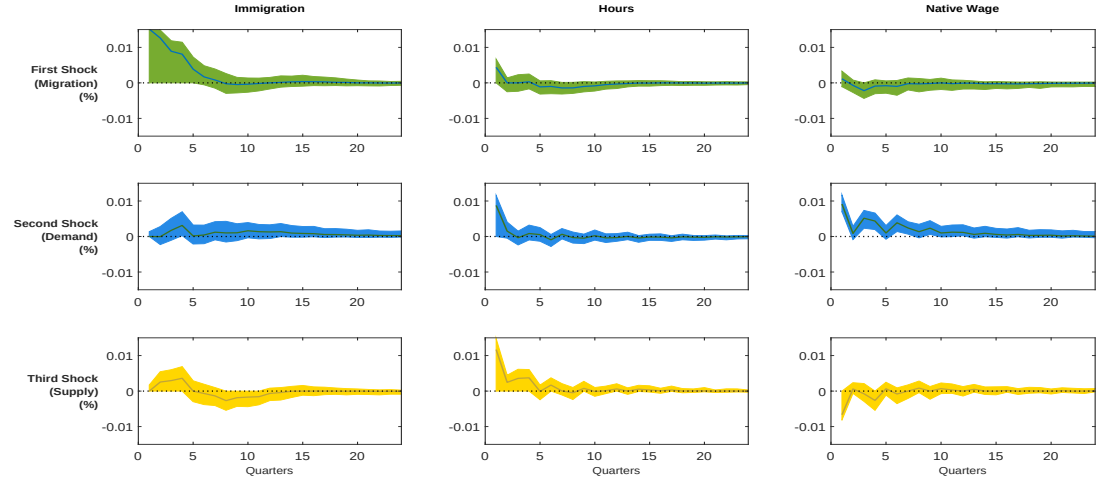
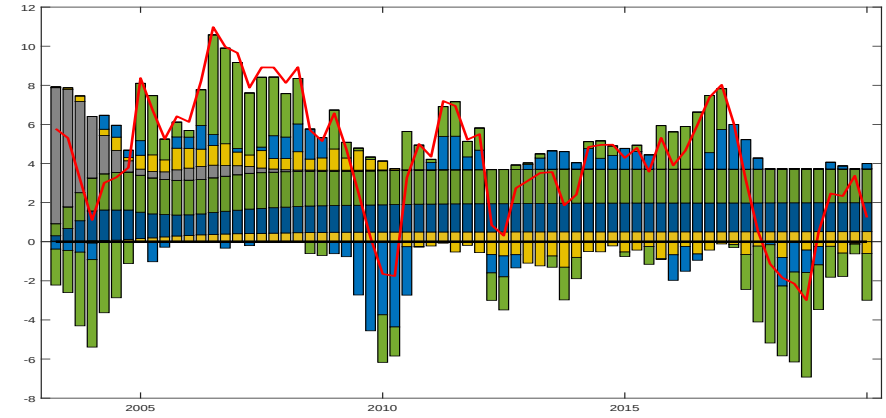


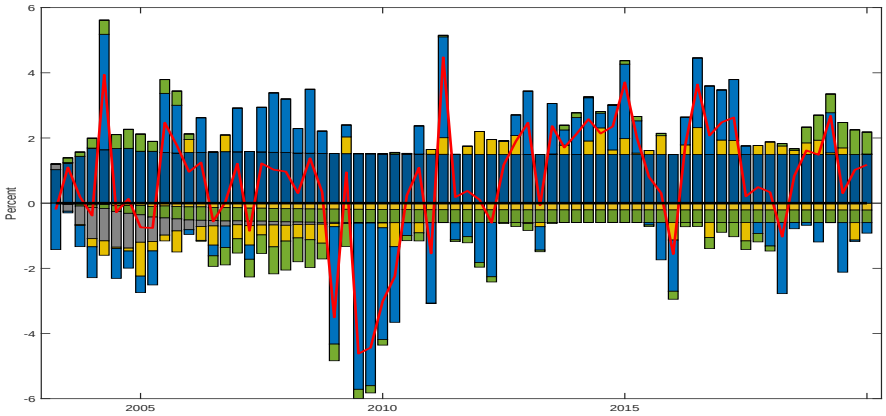
Figure 9 plots the impulse responses from three alternative identification schemes. Panel (a), shows the impulses from a Cholesky identification where the variables are ordered migration, hours, wages, Panel b) from a Cholesky identification where the variables are ordered wages, hours, migration, and Panel (c), from the a penalty function identification. The colors of the bars relate to the colors of the impulses in Figure 3.

Figure 10: Historical decomposition of aggregate variables - Cholesky Ordering wages, hours migration

(a) Aggregate migration



(b) Aggregate hours



(c) Aggregate native wages

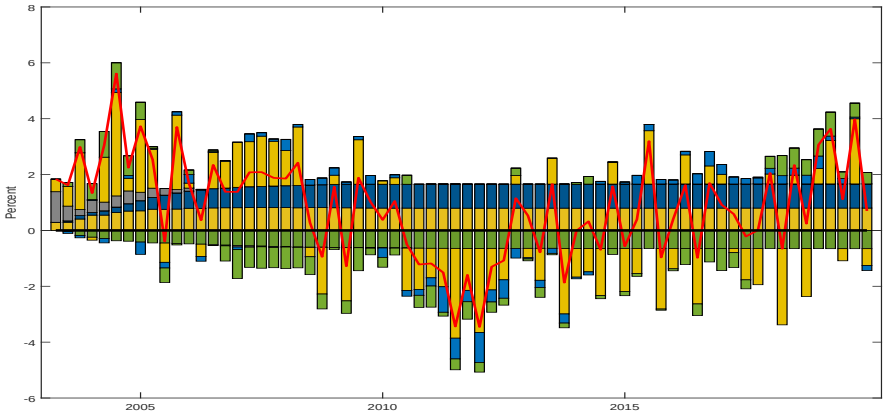


Figure 10 plots the median estimate of the historical contribution to aggregate native migration share growth, Panel (a), aggregate hours growth, Panel (b), and aggregate native wage growth, Panel (c), of the aggregate identified shocks, where the shocks are identified using Cholesky identifications where the variables are ordered wages, hours, migration. The colors of the bars relate to the colors of the impulses in Figure 3 for both the constant and error terms. The contribution of the initial condition is colored grey.

6 Conclusion

We started by noting that the literature on the labor market effects of immigration has consistently found only small effects of immigration on native wages. We have shown that the data is nonetheless consistent with immigration having significant adverse effects on native wages. This is because it may be that the negative effects of migration have been offset by positive contemporaneous demand and supply effects. We have presented a model of the UK labor market identified using standard macroeconomic assumptions where such effects do indeed occur. We have shown that this model also provides a plausible account of the evolution of the data over the sample period. Furthermore, we have shown that these effects differ across sectors, with unskilled manual sectors showing the largest adverse wage effects from immigration. Our results are robust to alternative identification approaches, but, of course, no identification approach is beyond question. Nevertheless our main result is clear. The empirical literature has frequently noted that its results are subject to the proviso that they are abstracting away from demand and sectoral heterogeneity effects. We have shown that not only is this proviso justified, but potentially these neglected effects may be important.

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A Appendix

A.1 Formulas used in Calculation

The formulas we use to calculate the impulse response functions and historical decompositions follow those of the literature see e.g. Hamilton (1994), Uhlig (2005) and Baumeister and Hamilton (2018).

The reduced form VAR of n dimensions and p lags can be written

$$\underset{(n\times 1)}{y_t} = \underset{(n\times 1)}{C} + \underset{(n\times n)}{B_1}\underset{(n\times 1)}{y_{t-1}} + \underset{(n\times n)}{B_2}\underset{(n\times 1)}{y_{t-2}} + \dots \underset{(n\times n)}{B_p}\underset{(n\times 1)}{y_{t-p}} + \underset{(n\times 1)}{u_t} \qquad u_t \sim \mathcal{N}(0, \underset{(n\times n)}{\Sigma}) \tag{A1}$$

This can be stacked and written as 1 lag VAR,

$$\underset{(np\times 1)}{\widehat{Y}_t} = \underset{(np\times 1)}{\widehat{C}} + \underset{(np\times np)}{F}\underset{(np\times 1)}{\widehat{Y_{t-1}}} + \underset{(np\times 1)}{u_t} \tag{A2}$$

where

$$\widehat{Y}_t = \begin{bmatrix} y_t \\ \vdots \\ y_{t-p+1} \end{bmatrix} \widehat{c} = \begin{bmatrix} C_{n\times 1} \\ 0_{(n(p-1)\times 1)} \end{bmatrix} \quad F = \begin{bmatrix} B_1 & \dots & B_p \\ I_{n(p-1)} & & 0_{n(p-1),n} \end{bmatrix} \widehat{u}_t = \begin{bmatrix} u_t \\ 0_{n(p-1),1} \end{bmatrix}$$

Iteration of equation (A2) forward implies that the observation $\widehat{Y_{t+s}}$ in period $t+s$ can be decomposed into three contributions, the initial conditions,the constant terms and the innovations in the previous s periods , i.e.

$$\widehat{Y_{t+s}} = \underbrace{F^s\widehat{Y}_t}_{\text{Initial Conditions}} + \underbrace{F^{s-1}\widehat{C} + F^{s-2}\widehat{C} + \dots + \widehat{C}}_{\text{constant terms}} + \underbrace{F^{s-1}\widehat{u_{t+1}} + F^{s-2}\widehat{u_{t+2}} + \dots + \widehat{u_{t+s}}}_{\text{Innovations}} \tag{A3}$$

The historical decomposition and counterfactual exercises are produced using equation (A3) where the contribution of the fundamental innovations use the formula $u_t = S^{-1}\epsilon_t$ following equation (**??**) in the text.

Iterating backwards into infinite history, $\widehat{Y}_t$ can be expressed as an $MA(\infty)$ process

$$\begin{aligned} \widehat{Y}_t =& \widehat{C} + F\widehat{C} + F^2\widehat{C} + \dots + \widehat{u}_t + F\widehat{u_{t-1}} + F^2\widehat{u_{t-2}} + \dots + \\ \widehat{Y}_t =& \widehat{\mu} + \Psi(L)\widehat{u}_t \end{aligned} \tag{A4}$$

Where $\mu = (I_n - A_1 - \dots A_p)^{-1}C$ and $\widehat{\mu} = [\mu' \ 0_{1\times n(p-1)}]'$ and where $\Psi(L)$ is an $MA(\infty)$ process. These can be written

$$\begin{aligned} y_t =& \mu + u_t + \Psi_1 u_{t-1} + \Psi_2 u_{t-2} + \Psi_3 u_{t-2} + \\ \widehat{Y}_t =& \mu + \Psi(L)u_t \end{aligned} \tag{A5}$$

where Ψ_j is the upper left $n \times n$ clock of matrix F^j, following Hamilton (1994).

A.2 Cholesky Factorization - Structural Interpretation

Cholesky factorization of the reduced form variance-covariance matrix, Σ, also has a structural interpretation. Since $u_t = L\epsilon_t$ premultiplying the reduced form VAR, equation (**??**), by the Cholesky factor L^{-1} gives

$$L^{-1}y_t = L^{-1}\tilde{C} + L^{-1}\tilde{B}_1 y_{t-1} + L^{-1}\tilde{B}_2 y_{t-2} + \dots L^{-1}\tilde{B}_p y_{t-p} + \epsilon_t \tag{A6}$$

Since L is lower triangular then L^{-1} is also lower triangular and equation (A6) has the form

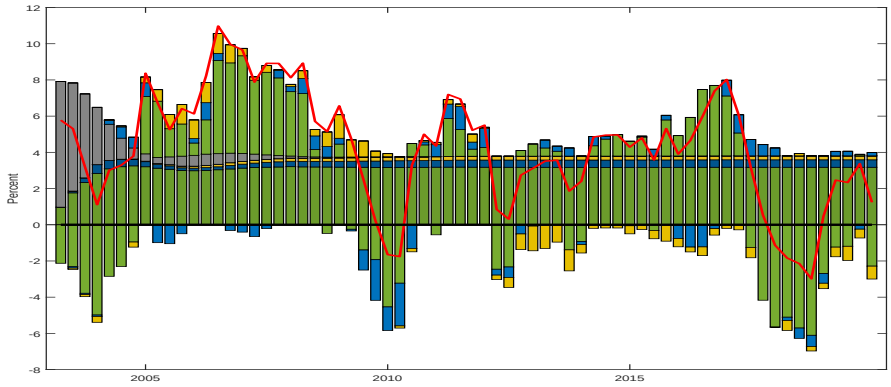
$$\begin{bmatrix} c_{11} & 0 & 0 & 0 & 0 & 0 \\ c_{21} & c_{22} & 0 & 0 & 0 & 0 \\ c_{31} & c_{32} & c_{33} & 0 & 0 & 0 \\ c_{41} & c_{42} & c_{43} & c_{44} & 0 & 0 \\ c_{51} & c_{52} & c_{53} & c_{54} & c_{55} & 0 \\ c_{61} & c_{62} & c_{63} & c_{64} & c_{65} & c_{66} \end{bmatrix} \begin{bmatrix} \text{Aggregate Migration Share} \\ \text{Aggregate Hours Worked} \\ \text{Aggregate Native Wage} \\ \text{Sectoral Migration Share} \\ \text{Sectoral Hours Worked} \\ \text{Sectoral Native Wage} \end{bmatrix} = L^{-1}C + \text{Lagged terms} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \epsilon_3 \\ \epsilon_4 \\ \epsilon_5 \\ \epsilon_6 \end{bmatrix} \tag{A7}$$

Equation (A7) implies that the variable ordered first in the VAR - aggregate migration share in this case - is only a function of lagged values of the other variables and $\epsilon_{1,t}$. Thus the order that the variables are placed in the VAR has a very significant impact on the interpretation and properties of each shock. In equation (A7), a natural interpretation of the first shock is as an exogenous aggregate migration shock. Similarly, the variable ordered second - Aggregate Hours Worked - is only a function of lagged values of the other variables and the contemporaneous value of aggregate migration (which is a function of $\epsilon_{1,t}$) and also of $\epsilon_{2,t}$. One interpretation of the second shock is therefore as a shock to aggregate hours net of the effects of the shock to aggregate migration. The same logic can be applied to the other shocks so that for the variable ordered last - the sectoral real wage in this case-, depends on all the current values of all variables and is therefore dependent on all contemporanous shocks $\epsilon_{1,t}, \epsilon_{2,t}, \epsilon_{3,t}, \epsilon_{4,t}, \epsilon_{5,t}$ and $\epsilon_{6,t}$. This has the same form as equation (3) above. However the property of the Cholesky factorization that only one shock's impulse responses, $\epsilon_{1,t}$, affects all the variables contemporaneously is often seen as a very strong restriction.

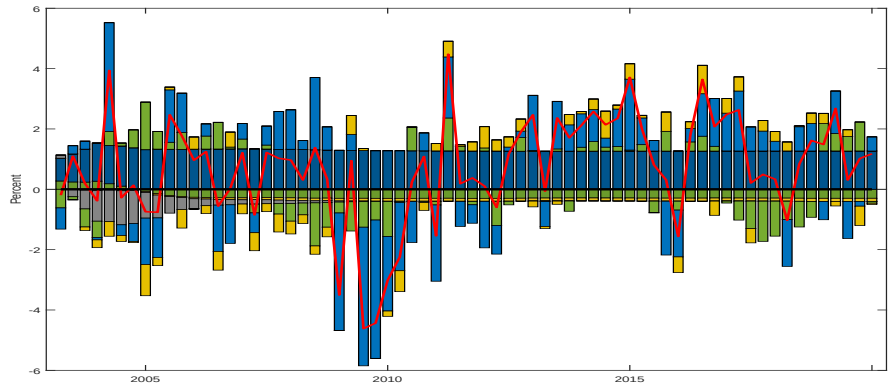
B Additional Figures

Figure B1: Historical decomposition of aggregate variables - Cholesky Ordering migration, hours, wages

(a) Aggregate migration



(b) Aggregate hours



(c) Aggregate native wages

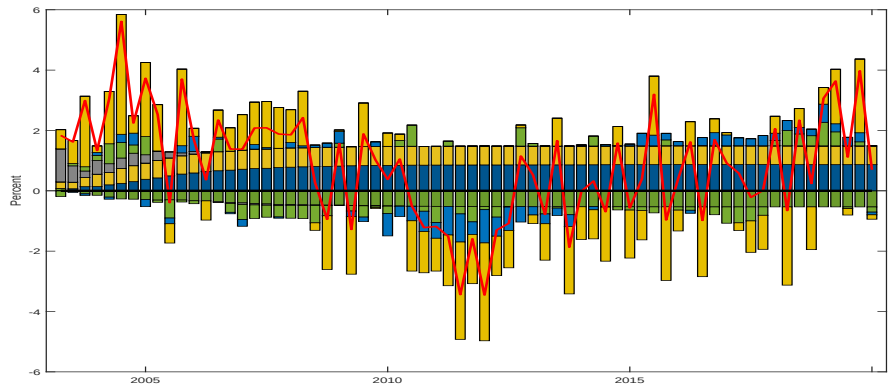
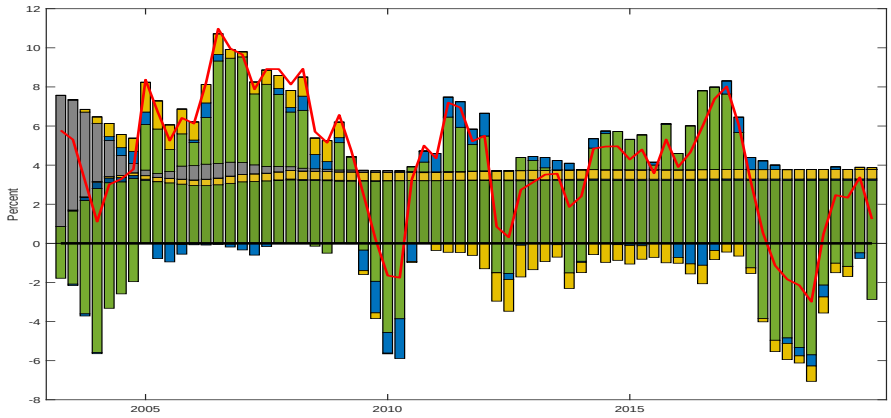


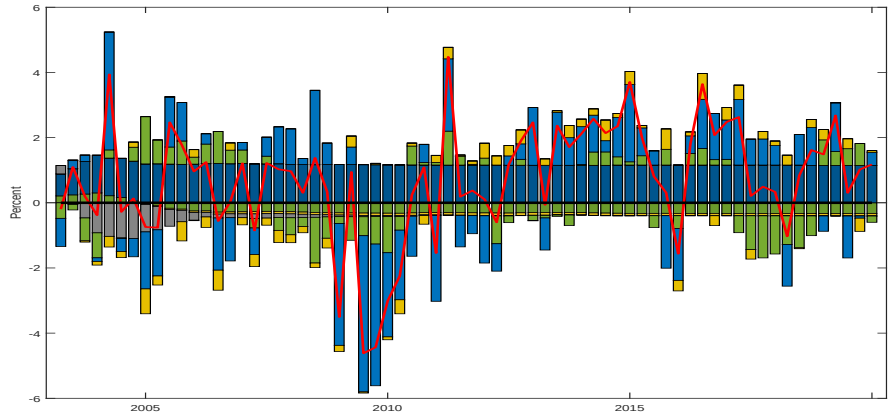
Figure B1 plots the median estimate of the historical contribution to aggregate native migration share growth, Panel (a), aggregate hours growth, Panel (b), and aggregate native wage growth, Panel (c), of the aggregate identified shocks, where the shocks are identified using Cholesky identifications where the variables are ordered migration, hours, wages. The colors of the bars relate to the colors of the impulses in Figure 3 for both the constant and error terms. The contribution of the initial condition is colored grey.

Figure B2: Historical decomposition of aggregate variables - penalty function identification

(a) Aggregate migration



(b) Aggregate hours



(c) Aggregate native wages

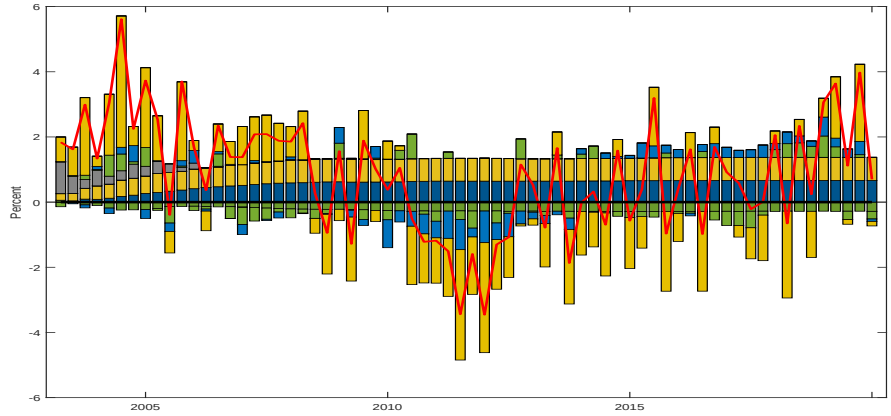


Figure B2 plots the median estimate of the historical contribution to aggregate native migration share growth, Panel (a), aggregate hours growth, Panel (b), and aggregate native wage growth, Panel (c), of the aggregate identified shocks, where the shocks are identified using a penalty function approach described in section 5. The colors of the bars relate to the colors of the impulses in Figure 3 for both the constant and error terms. The contribution of the initial condition is colored grey.

C Wage decompositions for all sectors

In Appendix C we plot the sectoral historical decompositions for native wages of all 35 estimated sectors. Those for unskilled manual sectors are given in Figure C1, those for skilled manual in Figure C2, those for the other non-manual sectors in Figure C3 and those for the professional sectors in Figure C4.

Figure C1: Historical Decompositions for native wages in the unskilled manual sectors using sign restriction.

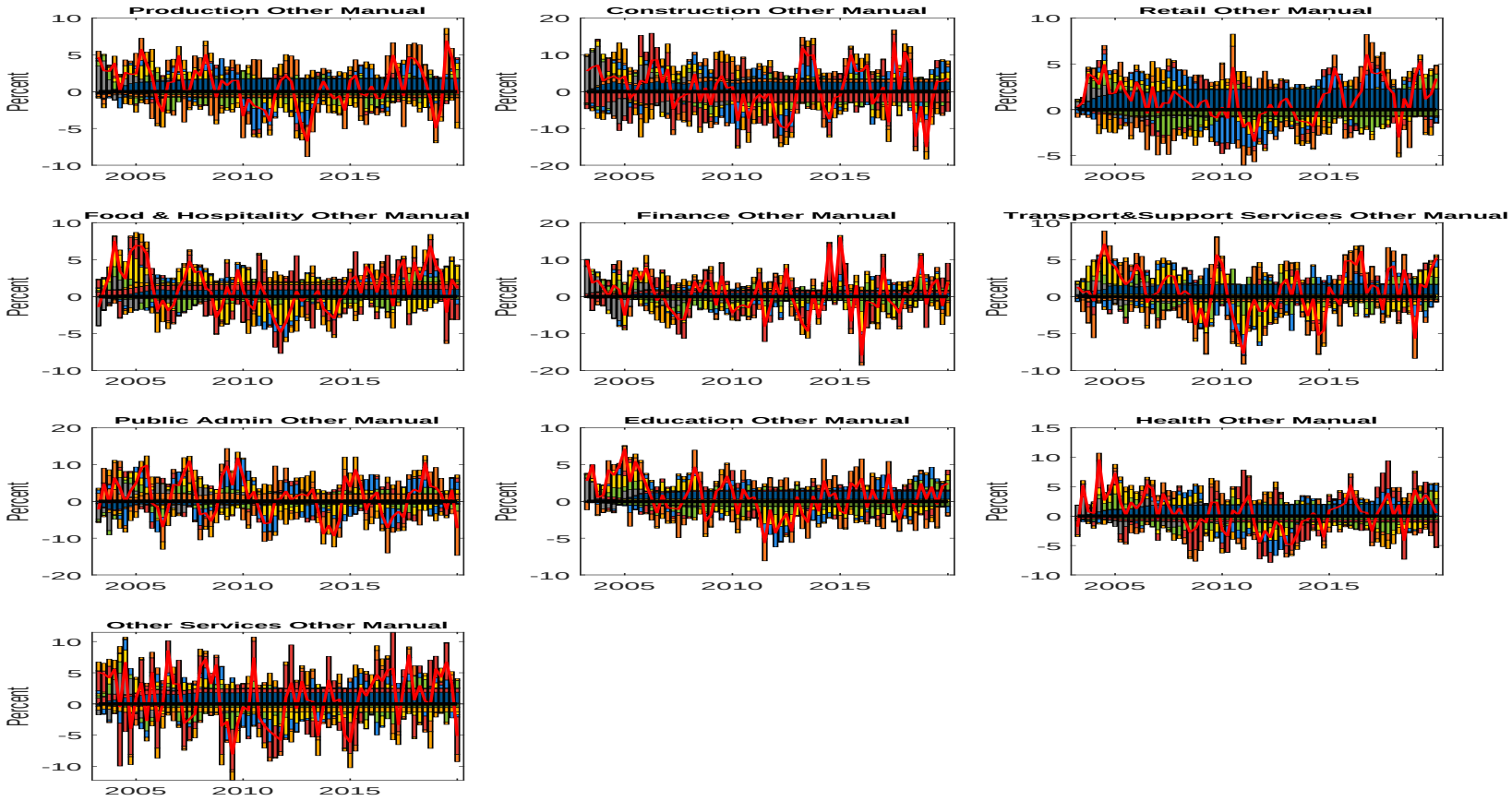


Figure C1 plots the median historical decompositions for native wage growth for all the unskilled manual sectors. These show the contribution of the six identified shocks and the constant terms and initial conditions. In each panel the red line plots data for sectoral native wage growth. The colors of the bars for the aggregate effects relate to the colors of the impulses in Figure 3, those for the sectoral shocks are shades of red and orange as described in section 4.3.

Figure C2: Historical Decompositions for native wages in the skilled manual sectors using sign restriction.

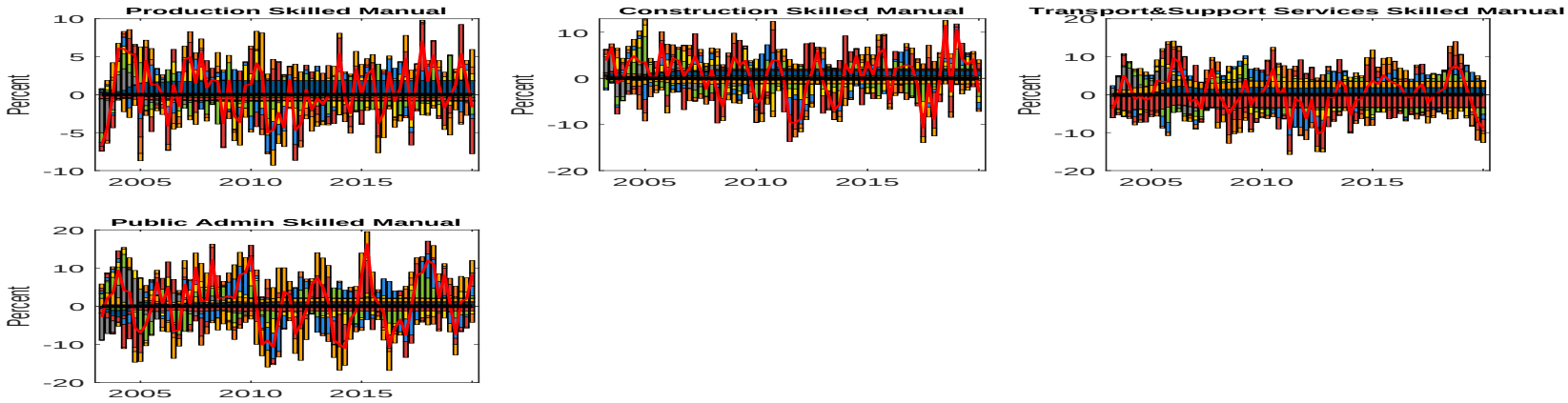


Figure C2 plots the median historical decompositions for native wage growth for all the skilled manual sectors. These show the contribution of the six identified shocks and the constant terms and initial conditions. In each panel the red line plots data for sectoral native wage growth. The colors of the bars for the aggregate effects relate to the colors of the impulses in Figure 3, those for the sectoral shocks are shades of red and orange as described in section 4.3. .

Figure C3: Historical Decompositions for native wages in the other non-manual sectors using sign restriction.

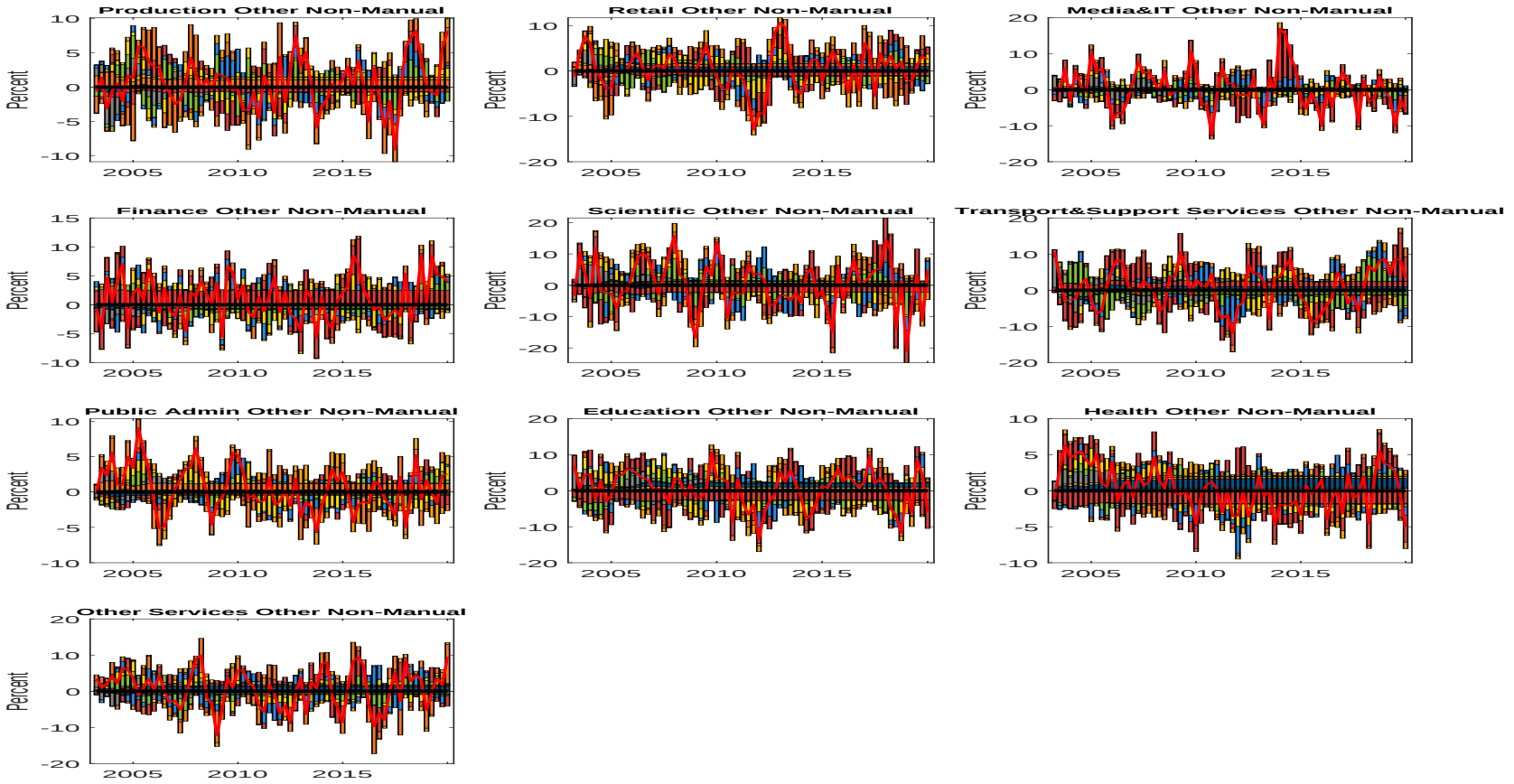


Figure C3 plots the median historical decompositions for native wage growth for all the other non-manual sectors. These show the contribution of the six identified shocks and the constant terms and initial conditions. In each panel the red line plots data for sectoral native wage growth. The colors of the bars for the aggregate effects relate to the colors of the impulses in Figure 3, those for the sectoral shocks are shades of red and orange as described in section 4.3.

Figure C4: Historical Decompositions for native wages in the Professional sectors using sign restriction.

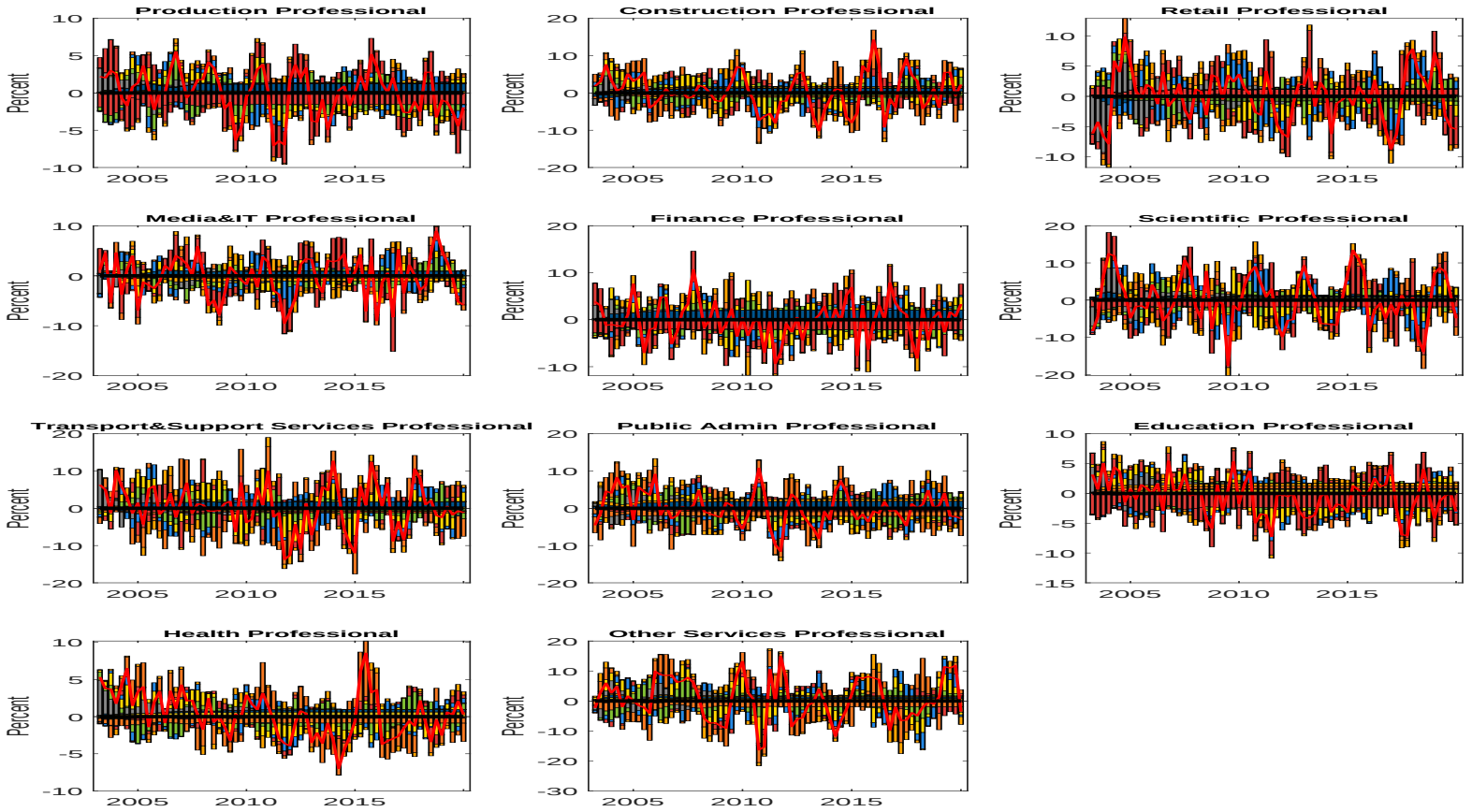


Figure C4 plots the median historical decompositions for native wage growth for all the professional sectors. These show the contribution of the six identified shocks and the constant terms and initial conditions. In each panel the red line plots data for sectoral native wage growth. The colors of the bars for the aggregate effects relate to the colors of the impulses in Figure 3, those for the sectoral shocks are shades of red and orange as described in section 4.3.