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RFBerlin
ROCKWOOL Foundation Berlin –
Institute for the Economy
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Gormannstrasse 22, 10119 Berlin
Tel: +49 (0) 151 143 444 67
E-mail: info@rfberlin.com
Web: www.rfberlin.com

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

Andrew Mountford† and Jonathan Wadsworth‡

† Royal Holloway, University of London and CReAM

‡ Royal Holloway, University of London, CEP(LSE), CReAM and IZA

Abstract

The empirical migration literature often identifies the labor market effects of immigration using exogenous variation of migration concentration across sectors or regions. However, this approach differences out macroeconomic effects which occur in all sectors. In this paper we apply macroeconomic time series methods to UK labor market variables from 2001-2019 for 35 different sectors, to model, for the first time, immigration, native wages and hours worked, as responding to demand, supply and immigration shocks at both aggregate and sectoral levels. The labor market is thereby modeled as being subject to multiple shocks at any one time, with individual shocks reinforcing and offsetting each other. Using a VAR approach, we find that the share of migrant labor is 'Granger caused' by other labor market variables which suggests that immigration is, in part, endogenously determined by aggregate demand and supply. However, it also retains a component which has a negative association between immigration and native wages, which may be thought of as a 'migration shock'. Using historical decompositions which decompose both the error terms and, novelly, the constant terms into their structural parts, we show that the 'migration shock' accounts for most of the change in migration share over the sample period and plays a significant negative role in the determination of native wage growth, particularly in unskilled sectors. However other contemporaneous shocks have offsetting positive associations between immigration and native wages, whose effects differ substantially across sectors.

Keywords: Immigration, Demand, Supply, VAR, Sectoral Heterogeneity
JEL codes: J6

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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 has identified the effects of immigration in the labor market using the variation of migration concentration across sectors or regions. However this approach differences out macroeconomic effects 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 (2023). 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 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. In this paper, we argue instead 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 demand. By the same token, effects which have been attributed to migration may in fact be the result of other shocks to the system.

We investigate empirically the relative importance of different types of shocks in explaining variation in key UK labor market variables. The UK is an important exemplar in this regard, exhibiting as it does, large variations in immigration rates, wages and employment across sectors and over time. 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

[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).

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 in the nature of the production process, and thereby in their use of different types of labor, and for other supply side reasons. 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. Borjas (1994) noted that "The size and composition of the immigrant flow are jointly determined by supply side considerations ....as well as by factors that determine the host country's demand for immigrants". Borjas' comments relate to the demand constraints at country-level imposed by visa quotas, which are common across industrialized economies.[3] The existence of shortage occupation lists as in Australia, Canada and the UK, can also be viewed as evidence of the importance of demand in influencing the level and type of immigration. There may also be dynamic demand responses to immigration. Ottoviano and Peri (2012) acknowledge this possibility, stating "We treat immigration as a labor supply shock, omitting any productivity impact that it may produce due, for example, to improved efficiency, choice of better technologies, or scale externalities". Peri, Rury and Wiltshire (2023) state that their results on the effect of immigration following Hurricane Marie are also consistent with a negative labor supply shock, offset by positive consumer demand shocks.

The assumption of exogenous labor supply shocks nevertheless still underlies the identification of immigration's effects on native workers' labor market outcomes in much of the empirical literature. Dustmann, Schönberg, and Stuhler (2016) state, "Any of the approaches we discuss slices the labor market into different sub-labor-markets and uses variation in the inflow of immigrants into these sub-labor-markets as an identification device. We assume here that the allocation of immigrants to these sub-labor-markets is (conditionally) independent of shocks to wages or employment of native workers (which could be achieved either through random allocation of immigrants, or by use of an appropriate instrument)... Studies that slice the labor market into skill groups instead typically assume that immigrant inflows are exogenous, an assumption that may be violated (Llull 2014)." Campo et al (2018) similarly argue "...there is significant consensus that immigrants select into labor markets with more

[3] The EU of course allows unrestricted mobility of individuals between member states.

favorable conditions (lower unemployment, higher wages) thus... immigration flows might be higher... to high productivity sectors which are more attractive and likely to be growing."

Alongside this issue of identification there also exists the possibility that immigration effects differ across skill levels. The existing literature has acknowledged the possibility of heterogeneous effects of immigration. Largely this has focused on different effects by migrant skill level and geographical origin, see e.g. Dustmann et al (2016), Ottoviano and Peri (2012) and Manacorda, Manning, and Wadsworth, (2012). In this paper we follow Mountford and Wadsworth (2023) in distinguishing between skill levels across industries. [4]

We show that these concerns about abstracting away from the effects of demand and sectoral heterogeneity may be well placed. We use a VAR approach where demand, supply and immigration shocks can occur simultaneously in every time period so that there is potential for multiple shocks to either offset or complement each other. 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 Furlanetto and Robstad (2019) on Norwegian data. However to our knowledge our paper is the first to employ a VAR framework that explicitly incorporates shocks at the sectoral as well as aggregate level.

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 six aggregate and sectoral shocks. 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.

VARs 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). This has typically been done using an arbitrary decomposition, namely the Cholesky factorization, of the variance-covariance matrix of the residuals of the VAR. Decomposition allows the creation of basis functions which together are able to reconstruct the observed time series. These reconstruc-

[4] Mountford and Wadsworth (2023) find that the effects of skilled immigration on training of the native workforce differs significantly across sectors, with in particular, 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.

tions, denoted 'historical decompositions', implicitly provide narrative descriptions of the evolution of the observed time series, as different basis functions play greater and lesser roles at different times. In the historical decompositions we make a novel addition by recognising that the total contribution of each shock also depends on its contribution to the constant term and duly decompose their effects on the constant. This gives a much deeper insight into the source of changes in wages, immigration and hours over time. We describe these historical decompositions of the evolution of native wages hours and immigration in detail in section 5 below. However, for an n variable VAR there are $n!$ different possible Cholesky factorizations, each of which will provide a different implicit narrative. In addition advocating causality based on any Cholesky factorization is problematic due to the strong restrictions it imposes on the responses of the identified shocks, see for example Uhlig (2005) and Baumeister and Hamilton (2015, 2019, 2024).

We therefore also employ the sign restriction identification methodology which 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 approach of Baumeister and Hamilton (2015, 2019, 2024) who show how one can incorporate beliefs and incomplete information about the effects of different shocks into the priors for the VAR's parameters in a Bayesian estimation procedure. The choice of which pattern of sign restrictions to impose is nevertheless subjective to some degree. In this paper we follow the macroeconomic literature and use minimal restrictions, so that, for example, a labor demand/business cycle shock is identified as a shock with a positive co-movement of native wages and hours. [5]

The minimal identifying assumptions we use still leave a lot of scope for interpretation. Should a shock which generates a positive co-movement of aggregate migration share, aggregate hours and native wages, be characterized as an exogenous aggregate labor demand shock? Macroeconomists are very confident that such a force should be present in the data, either as a macroeconomic demand or business cycle shock. The historical decompositions also support this interpretation, as this shock explains most of the variation in hours worked over the sample, with strong negative shocks in the period after the 2008 financial crisis. We are therefore happy to label this shock as an aggregate labor demand/business cycle shock,

[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 (2009) but we focus here on minimal assumptions. Results using the penalty function approach are available on request.

but we cannot rule out other possible interpretations.[6] Similarly, we label shocks with a negative association between aggregate immigration and aggregate native wages as a labor supply/migration shock in line with standard theory. The historical decompositions are also consistent with this interpretation, as this shock explains most of the variation in migrant share over the sample period with large negative shocks after the Brexit referendum. This is very intuitive. Again, however, of course, there are other possible interpretations.

In our final section we put some numbers on the extent of the wage effects of each identified aggregate shock using a counterfactual approach, where the contribution of one of the identified shocks is set to zero in an otherwise standard historical decomposition analysis. This exercise shows the estimated contribution of the left out shock to the observed time series. This is done without reference to a deep structural model and so one should not use this analysis to make statements like "If immigration was $x\%$ lower then native wages would be $y\%$ higher". However one can make statements like "At the model's median estimate, the contribution of the aggregate migration labor supply shock to native wage growth in sector A over the sample period was $x\%$ out of a total sectoral native wage growth of $y\%$." Indeed we find for certain sectors, such as the unskilled retail sector, that the absence of the shock that explains most of the variation in migration share, results in a native wage level more than a 15% higher by the end of the sample period. However in many professional sectors the absence of this migration shock has very little effect on the native wage path. This shows that an aggregate shock may have very different effects across sectors.

The paper is organized as follows. We first describe the data that underpin the analysis in section 2. We then describe the sectoral variation in native wage and immigration growth over the sample period in section 3 which is the focus of the paper. Section 4 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 presented in section 5.

[6] This shock will include the dynamic demand effects from the induced immigration.

Figure 1: Growth rates of immigration share, hours worked and average native real wages in the UK 2001-2020. We have used red lines for the data series in figures throughout this paper.

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 immigrants working. 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.[7]

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

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

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 Manual), and 13 industries.[8] 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.[9] The industry classifications also change in 2009 but we are able to correct for this using the mapping of Smith.[10] 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 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.[11] The aggregate versions of these variables are the aggregates of the sectoral variables weighted by their LFS population weights.

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 1 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 2001-2020 using UK LFS data. 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 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 2004q1-2016q2, 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.

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

[9] 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.

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

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

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 4, has developed methods to untangle the 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.

Table 1

Granger causality tests for aggregate labor market variables

	Time Period 2003q1-2019q4		**Time Period 2004q1-2016q2**	
Model:	**VAR(4)**	**VAR(4) with trend**	**VAR(4)**	**VAR(4) with trend**
	Chi-Sq	Chi-Sq	Chi-Sq	Chi-Sq
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, 2003q1-2019q4 and 2004q1-2016q2. ***,**, and * indicate significance at the 1%,5% and 10% level respectively.

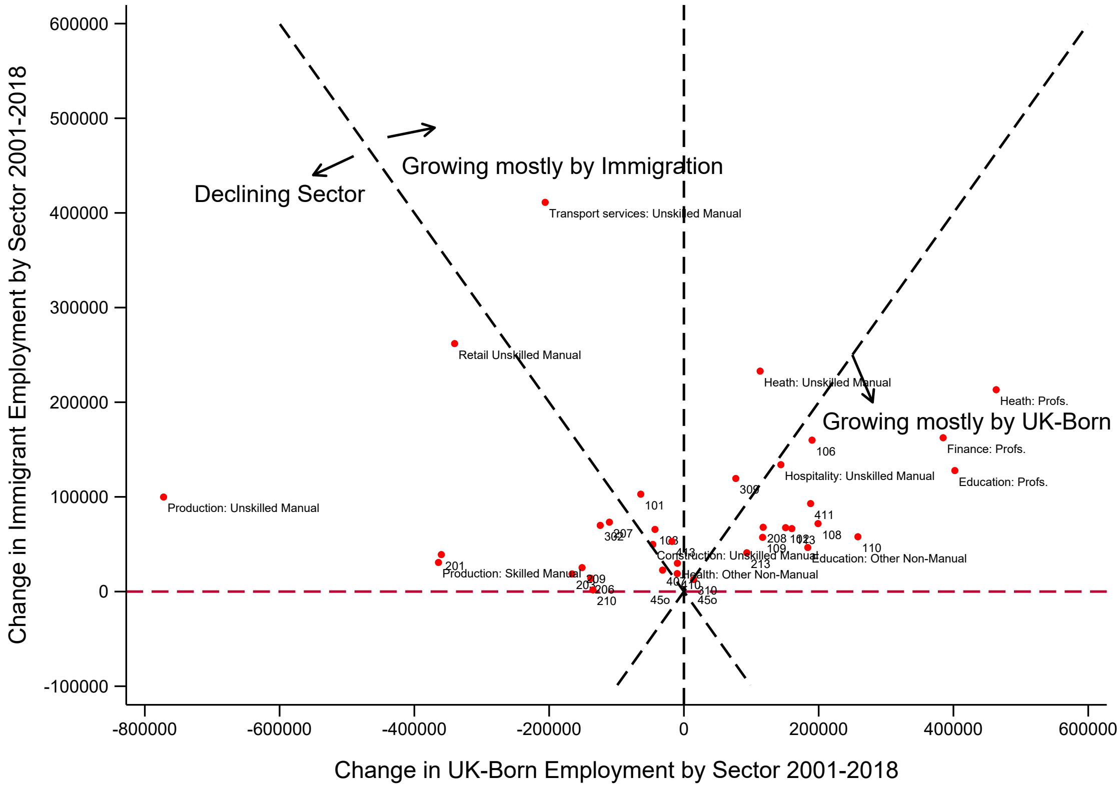


Figure 2: Change in UK-Born & Immigrant Employment by Sector 2001-2018

3 Sectoral variation in immigrant labor

To illustrate the degree of heterogeneity in the use of immigrant labor across sectors, Figure 2 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 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.[12] 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

[12] 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.

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 the Figure shows that there is substantial heterogeneity in changes in both employment and the immigrant share across 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 3 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.

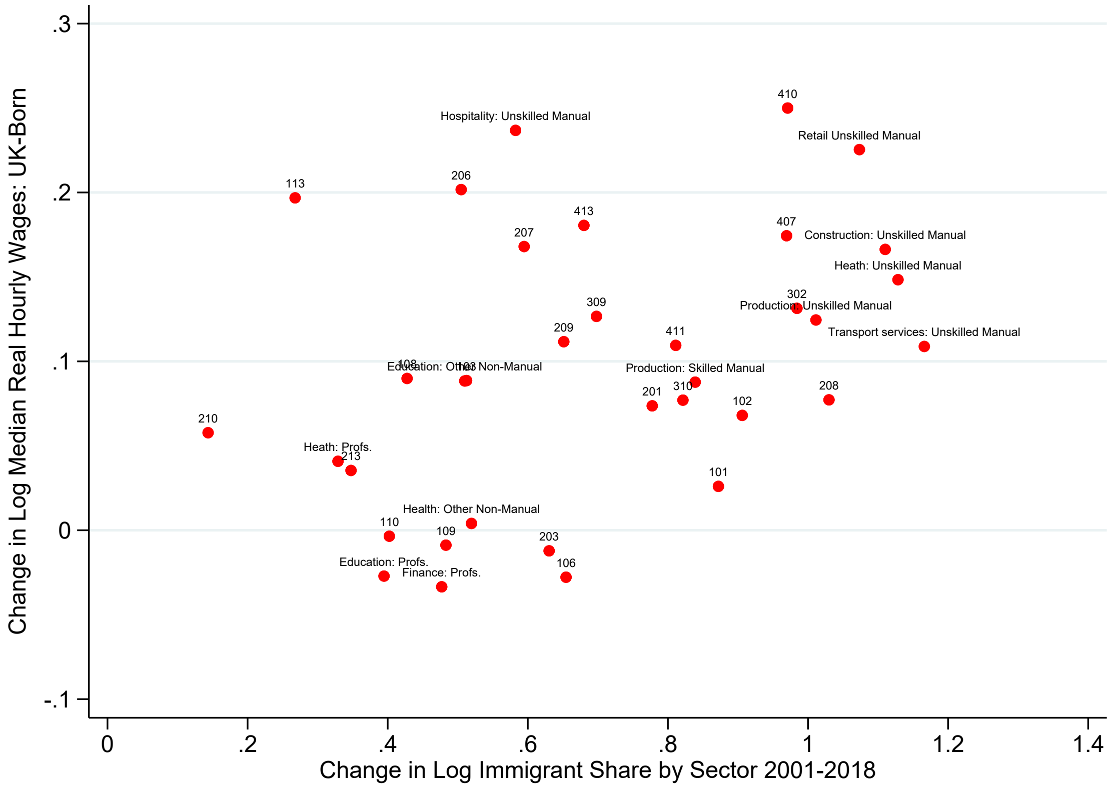


Figure 3: Log change in UK-born log real hourly wage & immigrant employment share by sector 2001-2018

4 Sectoral labor market dynamics with multiple causal factors

We argue in this paper that it is useful to exploit the information contained in the time series dimension of the data to model sectoral labor markets as being subject to multiple forces at any one time. For example, sectoral wages of native workers in period t, w_t^{sec}, may be subject to shocks from a combination of aggregate migration, $\epsilon_{aggM,t}$, aggregate supply, $\epsilon_{aggS,t}$, aggregate demand, $\epsilon_{aggD,t}$, sectoral migration, $\epsilon_{secM,t}$, sectoral supply, $\epsilon_{secS,t}$, and sectoral demand, $\epsilon_{secD,t}$, as in the following equation,

$$w_t^{sec} = \beta x_{t-1} + \alpha_1 \epsilon_{aggM,t} + \alpha_2 \epsilon_{aggS,t} + \alpha_3 \epsilon_{aggD,t} + \alpha_4 \epsilon_{secM,t} + \alpha_5 \epsilon_{secS,t} + \alpha_6 \epsilon_{secD,t} \qquad (1)$$

where α_i are parameters indicating the strength of each shock in determining native wages in this sector and where x_{t-1} is a vector of predetermined variables.

This type of wage equation corresponds to one of the equations in a structural VAR, where the predetermined variables are the constant term and the lags of the variables included in the VAR, denoted y, so that in equation (1), $x_{t-1} = [1, y'_{t-1}, \ldots, y'_{t-p}]'$, and x_{t-1} is an $((np+1) \times 1)$ vector where n is the number of variables and p is the lag length in the VAR.

A structural VAR is described by equation (2),

$$Sy_t = C + B_1 y_{t-1} + B_2 y_{t-2} + \cdots + B_p y_{t-p} + \epsilon_t \tag{2}$$

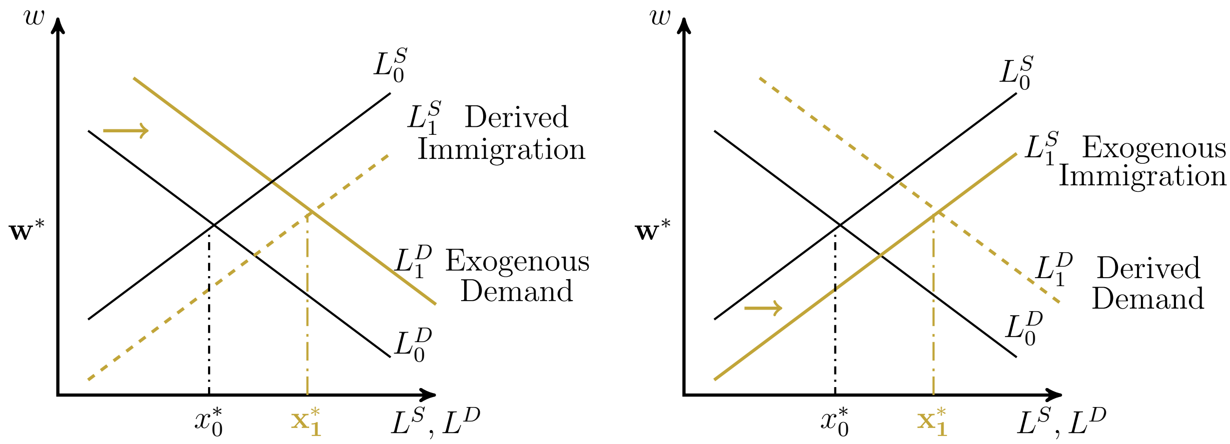
where S, is the $(n \times n)$ matrix of contemporaneous effects, C, is the $(n \times 1)$ vector of constants, B_i, are the $(n \times n)$ matrix of parameters for lag i, and ϵ_t, is the vector of the fundamental shocks on the VAR. The $(n \times n)$ variance covariance matrix for these shocks, $E[\epsilon_t \epsilon_t'] = D$, is assumed to be diagonal. The diagonal structure implies the shocks are 'fundamental' in the sense of not being associated with each other.

In our VAR model, for each sector we choose $p = 4$, for quarterly data, and $n = 6$, as we are interested in the interaction between 3 aggregate and 3 sectoral shocks on aggregate and sectoral variables. The six variables are the year on year difference of the logs of the economy-wide migration share, M_t^{agg}, economy-wide total hours worked, H_t^{agg}, economy-wide real wages of native workers, W_t^{agg}, 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 $y_t = (M_t^{\text{agg}}, H_t^{\text{agg}}, W_t^{\text{agg}}, m_t^{\text{sec}}, h_,^{\text{sec}} w_t^{\text{sec}})'$. The aggregate variables allow for the identification of economy-wide aggregate demand, supply and migration shocks while the presence of the sectoral variables allows for the possibility of sectoral demand, supply and migration shocks to also affect the outcome variables.

Baumeister and Hamilton (2015, 2019) show how one can incorporate prior beliefs about the signs and size of the coefficients in the contemporaneous effects matrix, S, into a Bayesian estimation procedure for the VAR. They derive a Metropolis Hasting algorithm for drawing from the posterior distribution for the parameters resulting from these priors. Baumeister and Hamilton (2015) describes this method in detail and so our exposition here can be brief. We use the programs supplied by Baumeister and Hamilton for the replication of Baumeister and Hamilton (2019) to estimate the model.[13] We also impose additional assumptions in the prior for the B parameters, namely we 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.

As a comparator, we also estimate the responses of the VAR using the Cholesky factor-

[13] We make 80,000,000 draws from the posterior for each sector discarding 64,000,000 draws as 'burn in' and retain every 4000th 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.



(a) Exogenous demand shock potentially causing increased immigration.

(b) Exogenous immigration shock potentially causing increased demand for labor.

Figure 4: Identification: which shocks matter most for changes in sectoral wages of natives?

ization as described below in section 4.1.1. 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).[14]

4.1 Identifying different structural shocks

Given the estimated model parameters and variance covariance matrix, the aim of identification is to define the different fundamental shocks which underlie the movement of each variable. This amounts to choosing the matrix, S, in the structural VAR described in equation (2). Given this matrix S, one can then calculate which shocks are most important for the variation of each variable, and also how they reinforce or offset each other. For example, as illustrated in Figure 4, one may be unsure whether demand shocks or migration shocks are most important in determining sectoral wage rates. An observed significant rise in hours worked occurring alongside little or no change in sectoral wages may be the result of a positive shock to the demand for labor which is responded to by an increase in the labor supply, including from immigration. This case is depicted in Panel a) of Figure 4. Equally, as depicted in Panel b), an exogenous shock to the labor supply which increases domestic labor demand in response could generate a similar effect.

Clearly this is not an exhaustive list of potential explanations for this relationship. In

[14] 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. We discuss the results for the Cholesky identification in Appendix B

Section 5 we compare the contribution of six identified shocks to the variation in native wage growth in each sector. Structural analysis uses economic theory to separate out multiple economic time series into their fundamental economic components. In our case it is often thought that some of migration is an exogenous shock to the system. If one also believes that migration will take one quarter to react to other shocks then the first row of the S matrix in the structural equation (2) will be zeros and the shock to the first equation can be thought of as an exogenous migration shock. This is the case in the Cholesky migration, described below section 4.1.1, where we label the first shock as a migration shock

However the assumption that migration will not react to business cycle shocks and supply shocks within a quarter is a strong one and so we also employ a weaker set of identifying assumptions using the sign restriction following the approach of Baumeister and Hamilton (2017,2024) as described in section 4.1.2.

4.1.1 Using the Cholesky factor

The Cholesky factorization of the reduced form's variance covariance matrix, Σ, is widely seen as a useful and transparent, if arbitrary, way of summarizing the data's dynamics. The reduced form VAR is given by multiplying equation (2) by the inverse of the S matrix,

$$y_t = S^{-1}C + S^{-1}B_1 y_{t-1} + S^{-1}B_2 y_{t-2} + \cdots + S^{-1}B_p y_{t-p} + u_t \tag{3}$$

where, therefore, $u_t = S^{-1}\epsilon_t$. Any symmetric positive-definite matrix, such as a variance covariance matrix, Σ, can be written as the product of a lower triangular matrix, L, known as the Cholesky factor, and its transpose, such that $LL' = \Sigma$. thus setting $S^{-1} = L$ is one possible form for the S matrix. Given an S matrix, the dynamics of the data can be summarized by six independent shocks, $\epsilon_1 \dots \epsilon_6$. Each shock is assumed to have a zero mean and a unit variance. Defining $\epsilon_t = [\epsilon_{1,t} \dots \epsilon_{6,t}]$, the independence of the shocks and their normalization implies that $E[\epsilon_t \epsilon_t'] = I_6$. The prediction errors of the VAR, u_t, is therefore mapped into these independent shocks via the equation $u_t = L\epsilon_t$, since $E[u_t u'] = LE[\epsilon_t \epsilon_t']L' = \Sigma$. The Cholesky factorization thus decomposes each variable's time series into the sum of responses to multiple independent shocks, see e.g. Baumeister and Hamilton (2024) or Sims (2003).

However because L is a lower triangular matrix, setting $S^{-1} = L$ implies that only one shock, $\epsilon_{1,t}$, affects all variables contemporaneously.[15] This is often seen as a very strong restriction. The sign restriction approach, described below, imposes looser restrictions so that, in our case, all sectoral variables can be affected contemporaneously by all shocks.

4.1.2 Using Sign Restrictions

Instead of assuming that S^{-1} is lower triangular, we can impose a looser set of restrictions that the VAR is lower block diagonal. Given that y_t is ordered, $y_t = (M_t^{\text{agg}}, H_t^{\text{agg}}, W_t^{\text{agg}}, m_t^{\text{sec}}, h_,^{\text{sec}} w_t^{\text{sec}})'$, this implies that aggregate variables are not contemporaneously affected by sectoral variables, following e.g. the intuition of Liu, Mumtaz and Theophilopoulou (2014). The S matrix therefore has the form

$$S = \begin{bmatrix} 1 & s_{MH} & s_{MW} & 0 & 0 & 0 \\ s_{HM} & 1 & s_{HW} & 0 & 0 & 0 \\ s_{WM} & s_{WH} & 1 & 0 & 0 & 0 \\ s_{mM} & s_{mH} & s_{mW} & 1 & s_{mh} & s_{mw} \\ s_{hM} & s_{hH} & s_{hW} & s_{hm} & 1 & s_{hw} \\ s_{wM} & s_{wH} & s_{wW} & s_{wm} & s_{wh} & 1 \end{bmatrix} = \begin{bmatrix} S_1 & 0 \\ S_2 & S_3 \end{bmatrix} \tag{4}$$

where S_1, S_2 and S_3 are the upper left, bottom left, and bottom right 3×3 submatrices of S. The first column of S gives the contemporaneous effect of aggregate migration on the other variables. Thus s_{HM} is the contemporaneous effect of aggregate migration on aggregate hours. Similarly the first row is the contemporaneous effects of other variables on aggregate migration, so that s_{MH} is the contemporaneous effect of aggregate hours on aggregate migration. Note that in the top left 3×3 block all three aggregate variables can contemporaneously affect each other, and the sectoral variables can be contemporaneously affected by all, aggregate and sectoral, variables.

The impact matrix of the fundamental shocks in the reduced form VAR, equation (3), is the inverse of the S matrix, S^{-1}. The lower block triangular nature of S implies that the determinant of S, $\det(S)$, is given by $\det(S) = \det(S_1)\det(S_3)$ and that S^{-1} can be decomposed into the product of 3×3 matrices.

$$S^{-1} = \begin{bmatrix} S_1^{-1} & 0 \\ -S_3^{-1} S_2 S_1^{-1} & S_3^{-1} \end{bmatrix}$$

[15] See Appendix A.2

Thus S^{-1} can be written

$$S^{-1} = \begin{bmatrix} \frac{1-s_{HW}s_{WH}}{\det(S_1)} & \frac{s_{MW}s_{WH}-s_{MH}}{\det(S_1)} & \frac{s_{MH}s_{HW}-s_{MW}}{\det(S_1)} & 0 & 0 & 0 \\ \frac{s_{WM}s_{HW}-s_{HM}}{\det(S_1)} & \frac{1-s_{MW}s_{WM}}{\det(S_1)} & \frac{s_{MW}s_{HM}-s_{HW}}{\det(S_1)} & 0 & 0 & 0 \\ \frac{s_{HM}s_{WH}-s_{WM}}{\det(S_1)} & \frac{s_{MH}s_{WM}-s_{WH}}{\det(S_1)} & \frac{1-s_{MH}s_{HM}}{\det(S_1)} & 0 & 0 & 0 \\ & & & \frac{1-s_{hw}s_{wh}}{\det(S_3)} & \frac{s_{mw}s_{wh}-s_{mh}}{\det(S_3)} & \frac{s_{mh}s_{hw}-s_{mw}}{\det(S_3)} \\ & -S_3^{-1}S_2S_1^{-1} & & \frac{s_{wm}s_{hw}-s_{hm}}{\det(S_3)} & \frac{1-s_{mw}s_{wm}}{\det(S_3)} & \frac{s_{mw}s_{hm}-s_{hw}}{\det(S_3)} \\ & & & \frac{s_{hm}s_{wh}-s_{wm}}{\det(S_3)} & \frac{s_{mh}s_{wm}-s_{wh}}{\det(S_3)} & \frac{1-s_{mh}s_{hm}}{\det(S_3)} \end{bmatrix} \quad (5)$$

Equation (5) demonstrates that a sign restriction on any one element of the S matrix does not necessarily imply a sign for the impact of any shock on any variable. Nevertheless sign restrictions can be imposed using the formulas for impact given in equation (5) during the sampling procedure for the elements of S, so that e.g. the restriction that the 4th ordered shock has a positive impact on sectoral hours and a positive impact on sectoral native wages, are the restrictions that $\frac{s_{wm}s_{hw}-s_{hm}}{\det(S_3)} > 0$ and $\frac{s_{hm}s_{wh}-s_{wm}}{\det(S_3)} > 0$. We order the shocks so that the aggregate migration shock is placed first in the ϵ_t vector, so that $\epsilon_t = (\epsilon_{aggM,t}, \epsilon_{aggS,t}, \epsilon_{aggD,t}, \epsilon_{secM,t}, \epsilon_{secS,t}, \epsilon_{secD,t})'$. Thus the sign restrictions for the aggregate migration shock are in the first column of S^{-1}.

The sign restrictions we impose in the structural model are described in equation (6), which omits the constant and lagged terms in equation (3) for ease of exposition. Thus the sign restrictions for a positive aggregate demand shock, in column 3, are that it has a positive impact effect on aggregate immigration, aggregate hours worked and aggregate real wages of natives. The aggregate supply shock in column 2 is identified as a shock which increases aggregate hours worked and reduces the aggregate real wage of natives on impact. The aggregate migration shock in column 1 is identified as a shock which increases aggregate migration share and hours worked on impact. There are no restrictions on the responses of other variables which is often referred to as being 'agnostic' about the responses of unrestricted variables to a shock. Note that the sign restrictions described by equation (6) and discussed in section 5.1.1 do not completely pin down the interpretation of these shocks. In particular, as we discuss below in section 5, the sign restrictions do not impose a direction of response of migration to a supply shock and so if the response of migration to the second shock is positive then this too could be interpreted as a migration shock.

$$\underbrace{\begin{bmatrix} \text{Aggregate migration share} \\ \text{Aggregate hours worked} \\ \text{Aggregate native wage} \\ \text{Sectoral migration share} \\ \text{Sectoral hours worked} \\ \text{Sectoral native wage} \end{bmatrix}}_{y_t} = \underbrace{\begin{bmatrix} + & \text{none} & + & \text{none} & \text{none} & \text{none} \\ + & + & + & \text{none} & \text{none} & \text{none} \\ \text{none} & - & + & \text{none} & \text{none} & \text{none} \\ \text{none} & \text{none} & \text{none} & + & \text{none} & \text{none} \\ \text{none} & \text{none} & \text{none} & \text{none} & + & + \\ \text{none} & \text{none} & \text{none} & \text{none} & - & + \end{bmatrix}}_{S^{-1}} \underbrace{\begin{bmatrix} \epsilon_{aggM,t} & \text{(Agg. Mig./Supply Shock)} \\ \epsilon_{aggS,t} & \text{(Agg. Supply/Mig. Shock)} \\ \epsilon_{aggD,t} & \text{(Agg. Demand Shock)} \\ \epsilon_{secM,t} & \text{(Sec. Migration Shock)} \\ \epsilon_{secS,t} & \text{(Sec. Supply Shock)} \\ \epsilon_{secD,t} & \text{(Sec. Demand Shock)} \end{bmatrix}}_{\epsilon_t} \quad (6)$$

We do not impose the same sign restrictions at the sectoral level as at the aggregate level. Thus for immigration, at the aggregate level it is intuitive that an increase in aggregate immigration should increase aggregate hours. However this need not be the case for every sector. As discussed above in section 3, in some sectors increased immigration may be associated with reduced total hours as migrant labor offsets an outflow of domestic labor. Thus the sectoral migration shock is simply restricted to increase the sectoral migrant share in equation (6). Similarly sectoral demand shocks are not required to increase sectoral migration shares.

Different identifying assumptions, will imply different roles for the identified shocks in contributing to the observed time series. Baumeister and Hamilton (2015, 2019) show how one can go further and tighten the identification by incorporating knowledge about the likely sizes of these S matrix parameters (elasticities) into the priors for these parameters. We do not do this in this paper as the incorporation of sector specific information for 35 sectors is beyond the scope of this paper. We therefore employ loose priors for all these coefficients, and leave the analysis employing more informative tighter priors for future work.[16]

4.2 The structural model: historical decompositions and counterfactuals

Each estimated draw of the S matrix allows the construction of a time series of fundamental shocks, ϵ_t, from the estimated reduced form errors, u_t, via the formula, $\epsilon_t = Su_t$. The observed time series can then be reconstructed using these time series of fundamental shocks by recursive iteration of equation (2) as described in Hamilton (1994) and briefly in Appendix A.1. This is the historical decomposition.

We illustrate our results with 'counterfactual analysis'. The counterfactual error, ϵ_t^{CF} from setting one of the shocks to zero, is simply ϵ_t with the corresponding element set to

[16]The priors are a students t distribution, $t_\nu(\mu, \tau^2, \nu)$ with $\mu = 0, \tau = 100$ and $\nu = 3$.

zero- e.g. the second element of ϵ_t is set to zero for all t, if the influence of second fundamental shock on the observed time series is being removed. The counterfactual reduced form residual will then be given by $u_t^{CF} = S^{-1}\epsilon_t^{CF}$. The structural constant terms C in equation (2) can be constructed in the same way by multiplying the estimated reduced form constant by S. The counterfactual constant term, C^{CF} will then be C with the element corresponding to the shock replaced by zero. The counterfactual reduced form constant term is then given by the vector $S^{-1}C^{CF}$. 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 shock over the sample period. One aspect that is not typical is the accounting of the contribution of the specified shock to the steady state growth rate of each variable via its contribution to the constant terms in the VAR. This is important and is often ignored by the literature.

5 Results

In this section we discuss the results from the VARs identified under the Baumeister and Hamilton sign restriction methodology described above in section 4.1.2.[17] We first discuss the results for aggregate variables in section 5.1 and then the results at the sectoral level in section 5.2. In each case we first describe the impulse response functions. These are the building blocks for the discussion of the historical decompositions of the data which will be the focus of our attention. Historical decompositions show for each data series, the contribution of each of the six identified shocks at each point in time. 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 put numbers on the contribution of each identified aggregate shock to each outcome variable in section 5.1.3, where we apply the 'counterfactual analysis' described above in section 4.2.

[17] We discuss the results for the Cholesky identification, which are very similar, in Appendix B

Figure 5: Impulse responses of aggregate variables to aggregate shocks

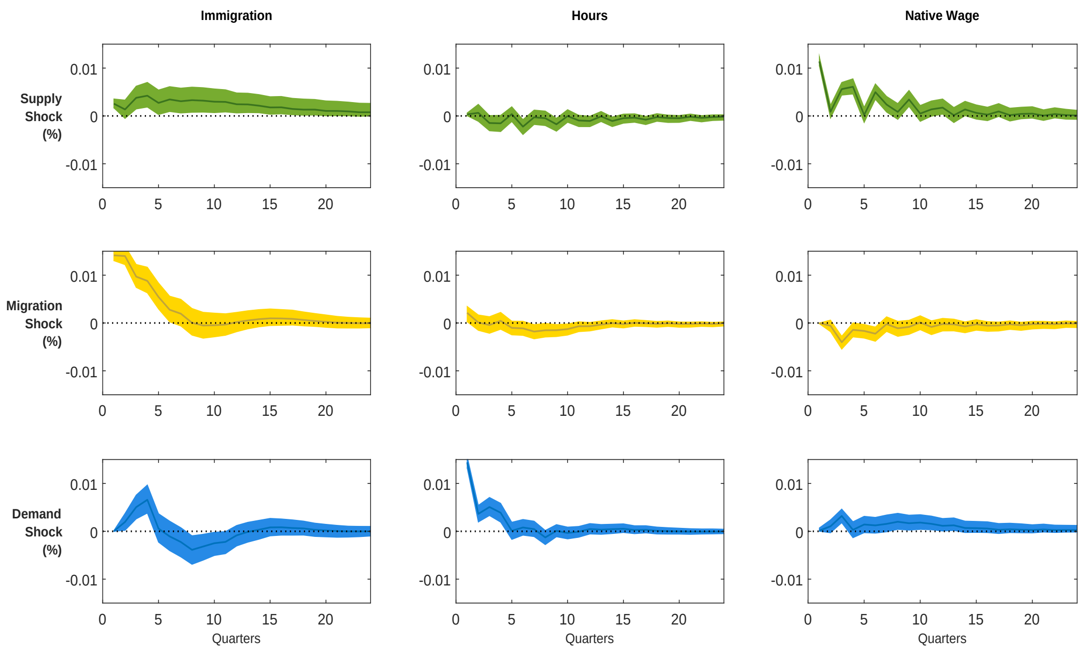


Figure 5 plots the impulse responses of the aggregate variables to aggregate shocks for the unskilled manual sectors using the sign restriction approach of section 4.1.2. The impulses of the supply shock are colored green those of the migration shock colored yellow and those of the demand shock colored blue. The shaded region is the area between the 16% and 84% quantiles of the posterior distribution with the median colored in a darker shade.

5.1 Results for aggregate shocks

In order to uncover the dynamic effects of our identified shocks on native wages, immigration and hours and the relative importance of each shock, we first present impulse response functions before discussing the historical decompositions of the data and the estimates of the relative contribution of each shock to each series.

5.1.1 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 standard deviation innovation for each of the identified shocks.[18] This is done for each draw from the posterior distribution of the parameters and so results in a distribution of impulse responses. In Figure 5 we plot the subset of responses for the aggregate variables to aggregate shocks. These Figures plot 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.[19] We have colored the responses to each shock differently so that when we

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

[19] As Figures B3 and 10 show the aggregate responses from other sectors are almost identical.

use the same colors for each shock in the historical decompositions in Figures 6 and 7, the contribution of each shock is clear.

The second identified shock in Figure 5, colored yellow, has sign restriction described in equation (6). As stressed in section 4.1.2, these sign restrictions allow the interpretation of this shock as a supply shock or a migration shock, but the strong response of migration to this shock suggests that a migration shock is the better characterization. Indeed the historical decompositions in Figures 6 and 7 below, show that this shock explains most of the variation in migration share over the sample period. Therefore, henceforth we will refer to this shock as a migration shock. The impulse response of migration share growth is strongly positive for about two years and the response of wage growth is negative for over a year after impact. The response of hours is very small. It is restricted to be positive on impact but it then immediately straddles the zero line. The positive association between migration and hours and wages are instead accounted for by the demand shock.

The third identified shock in Figure 5, colored blue, is the aggregate demand shock with sign restrictions described in equation (6). 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 shocks as a business cycle/demand shock is reinforced by the historical decompositions in Figures 6 and 7 below, which show that this shock explains most of the variation in hours over the sample period.

The first identified shock, colored green, is the least intuitive of the impulse responses. As stressed in section 4.1.2, the sign restrictions described in equation (6) are consistent with an interpretation as a supply shock or a migration shock. The historical decomposition in Figure 6 below, shows that this shock explains most of the variation in aggregate native wages but not of migration share. Figure 7 and the counterfactual analysis in section 9b show that the effect of this shock on long run wage growth is small. We therefore interpret this shock as a temporary supply, or positive productivity, shock which has a positive association with migration.

We asked at the outset whether immigration could be thought of as an exogenous shock. The impulses responses in Figure 5 suggest that aggregate immigration is influenced by shocks that could be considered aggregate supply, colored green, and aggregate demand, colored blue. However the yellow colored shock has the characteristics of what could be thought of as an exogenous migration shock. Thus aggregate migration seems to be influenced by both supply and demand as well as its own dynamics.

This is of key importance. It shows that there exists a decomposition of the data where one of the key components, the yellow colored shock, has negative association between immigration and native wages, alongside other shocks with a positive association. The historical decompositions described in the section 5.1.2 below, show how important each shock is in describing the underlying data and in section 5.1.3 we quantify the importance of each shock to native wage growth over the sample period. As we will show in some sectors, particularly unskilled manual sectors, the negative influence of the migration shock has been considerable.

Nevertheless, to reiterate, the impulse responses in Figures 5 still leave a lot of room for interpretation. The role of judgment in the labeling of the underlying structural shocks demonstrates, as in Baumeister and Hamilton (2019) and Uhlig (2005), that macroeconomic theory by itself is not sufficient to label the effects of any particular shock definitively. Thus if one is wanting a clearer result on the percentage of native wage growth 'caused' by migration then more information and/or tighter restrictions are needed. As described in section 4.1.2, the structural approach of Baumeister and Hamilton (2015, 2019) is designed to be able to incorporate such additional information, although doing so for 35 different sectors would be both challenging and debatable.

5.1.2 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.[20] These contributions depend on raised powers of a matrix of autoregressive parameters and will therefore differ across sectors. The contribution of each shock is highly related to its impulse response function, as described in e.g. Hamilton (1994). We discuss the historical decompositions aggregate variables in terms of aggregate shocks in Figure 6 and then emphasize the contribution of structural constant terms in the historical decompositions in Figure 7. The contribution of the constant terms will be very important for our counterfactual analysis.

The historical decompositions in Figure 6 are shown as a stacked bar chart, using the median responses. The observed data for each time series is plotted as a red line. The

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

sum of the stacked historical decompositions in each time period match each observed data series very well.[21] In each panel of Figure 6 we have colored the contribution of the shock to match those of impulse responses in Figure 5. Thus the contribution of the aggregate demand/business cycle shock is colored blue and the contribution of the shock where there is a negative association between migration and native wages is colored yellow. The contribution of the initial conditions and the constant term are colored grey and light grey respectively.

Panel a) of Figure 6 shows the historical decomposition for aggregate migration. This shows that the constant term explains a lot of the growth of migration share. However there is significant variation around this constant growth rate and this is mostly accounted for by the yellow shock which justifies the interpretation of this shock as an aggregate migration shock. In short aggregate migration is mostly driven by its own dynamics. However, aggregate immigration is also influenced by demand, particularly the significant negative shock after the 2008 financial crisis and after the Brexit referendum and by supply which has a positive effect before the financial crisis and negative afterwards.

Panel b) of Figure 6 shows the historical decomposition for aggregate hours. Again this shows a significant constant term but with relatively large variation around it. The dominant shock driving these variations in aggregate hours is the blue colored demand shock. The dominance of this shock is consistent with the Granger casuality results presented in Table 1 which showed that hours Granger caused the other data series but the other series did not Granger cause 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 small contributions comparatively. As we remarked in our discussions of the impulse responses above, the demand shock accounts for almost all of the positive correlation between hours and migration.

Panel c) of Figure 6 shows that the growth rate of native wages is mostly determined by the green colored supply shock and the constant term, although all three shocks play a role. The blue colored demand shock plays an important role in the period following the financial crisis of 2008, and the yellow colored migration shocks, play a significant part in native wage growth dynamics being notably negative around the time of the Brexit referendum (June 2016) and then having a positive, contribution afterwards which is all intuitive.

It is very important to note that a positive contribution of a yellow shock means that effect on native wages is less negative than expected. It does not necessarily mean that

[21] The sum of the median contributions do not necessarily sum to the original, see Bergholt, et al (2024), but as Figure 6 shows the match is quite close.

the total contribution of this shock to native wages is positive. The total contribution of each shock also depends on its contribution to the constant term whose total contribution is shaded grey in Figure 6. The same matrix S^{-1} which multiplies the fundamental shocks in equation (3) also multiplies the structural constant terms, as described e.g in Hamilton (1994). Thus when you are decomposing the reduced form error terms into their constituent fundamental terms you will also be decomposing the reduced form constant terms into their constituent fundamental parts, using precisely the same mapping. There is therefore the same correspondence - identification - between the structural constant terms and the reduced form constant terms as there is between the structural shocks and the reduced form disturbances. In Figure 7 we make this explicit and decompose the constant term in the same way as we do the variation.

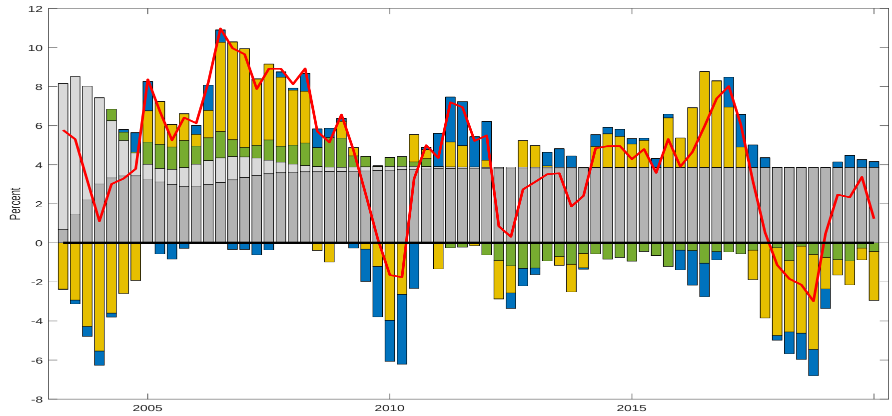
Panel a) of Figure 7 shows that the part of constant term associated with the migration shock, which we have also colored yellow, explains most of the constant growth rate of migration share. However there is a small positive contribution of the blue constant term associated with the growth of hours and the green constant term associated with the growth of wages. This reinforces the interpretation that migration is mostly determined by its own exogenous dynamics, with exceptions around the financial crisis and Brexit.

Panel b) of Figure 7 shows that the part of constant term associated with the demand shock, which we have also colored blue, explains most of the constant growth rate of hours. However there is a small negative contribution of the yellow constant associated with positive migration growth.

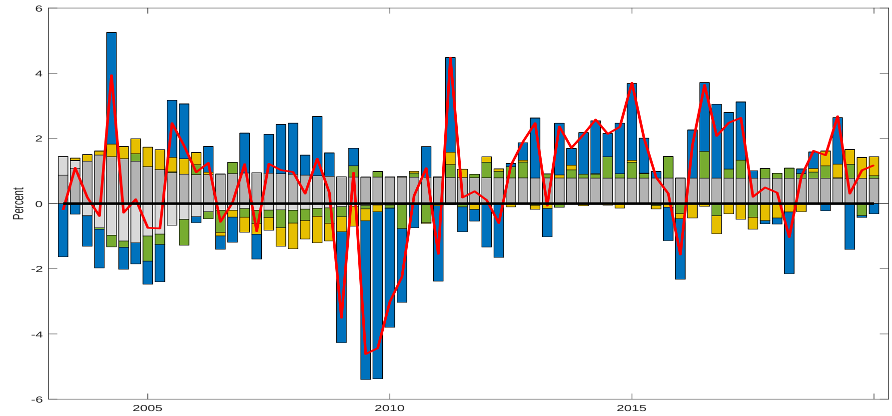
Panel c) of Figure 7 shows that the constant growth rate of wages is the product of two significant offsetting forces. The demand constant term has a significant positive effect on wage growth whereas the migration constant term has a significant negative effect.

Figure 6: Historical decomposition of aggregate variables using sign restriction approach

(a) Aggregate migration



(b) Aggregate hours



(c) Aggregate native wages

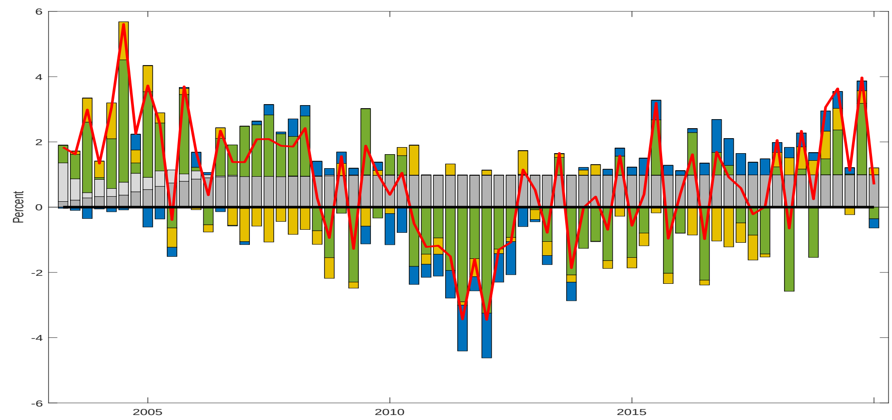
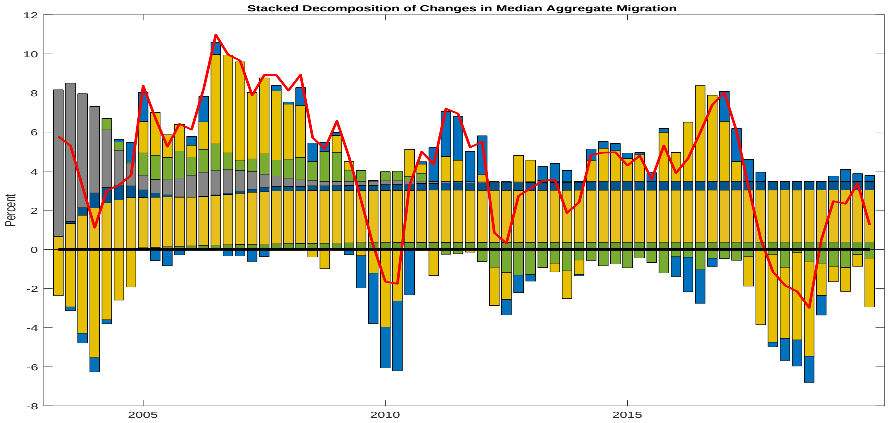


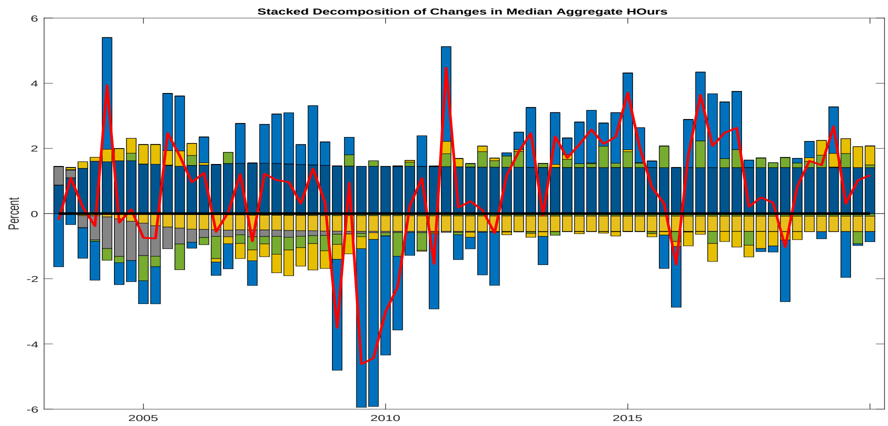
Figure 6 plots the median estimate of the historical contribution to aggregate native migration share growth (Panel a)), aggregate hours growth (Panel b)) and aggregate native wage growth (Panel c)) of the aggregate identified shocks, the initial conditions and the constant term, using the sign restriction methodology of section 4.1.2. The decompositions are taken from the unskilled transport services sector. In each panel the red line plots data for each series. The colors of the bars relate to the colors of the impulses in Figure 5.

Figure 7: Historical decomposition of aggregate variables including constant decomposition

(a) Aggregate migration



(b) Aggregate hours



(c) Aggregate native wages

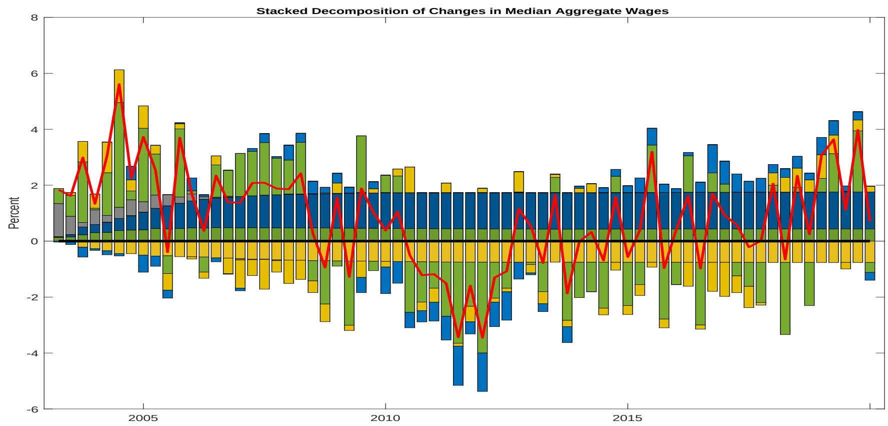


Figure 7 plots the same historical decompositions as Figure 7 but including the decompositions of the constant terms as discussed in the text. The decompositions are taken from the unskilled transport services sector. In each panel the red line plots data for aggregate native wage growth. The colors of the bars relate to the colors of the impulses in Figure 5.

5.1.3 How large are the effects? - a counterfactual analysis

Figure 7 shows how our analysis has allowed each data series to be decomposed into three constituent parts, related to the fundamental shocks described in section 5.1.1. Two of these constituent parts have intuitive interpretations as exogenous migration shocks and labor demand or business cycle shocks. However, to reiterate, these are not the only interpretations and there are many other possible decompositions of the data.

In this section we quantify the effects of these fundamental shocks on each observed data series. We do this by setting the contribution of each shock, one at a time, to zero and then recalculating each time series as per a historical decomposition as described in section 4.2. The difference between this counterfactual time series and the observed time series highlights the contribution of the left-out shock to the observed time series.[22] As stressed in section 4.2, this 'counterfactual' is done without reference to a deep structural model and so one should not use the analysis to make statements such as 'If immigration was $x\%$ lower then native wages would be $y\%$ higher'. However one can make statements, such as 'At the model's median estimate, the contribution of the immigration shock to wage growth over the sample period in sector A was $x\%$ out of a total wage growth of $y\%$'. Indeed we find that for several sectors, particularly unskilled manual sectors, the immigration (yellow) shock accounts for a negative 20% or more growth in native wages. i.e. in the counterfactual series, native wages in some sectors are 20% or more higher at the end of the sample period than in the observed data. We present the results of this exercise in two ways, graphically, in Figure 8, and numerically in Table 2.

[22] The median percentage counterfactuals do not vary much across runs. This is shown in Figure C1 and Table C3 in the appendix C. The Cholesky identification approach, which draws directly from the posterior, has smaller simulation error, and has very similar results. These are presented in Appendix A.2.

Figure 8: Counterfactual for aggregate native wage growth with no migration shock

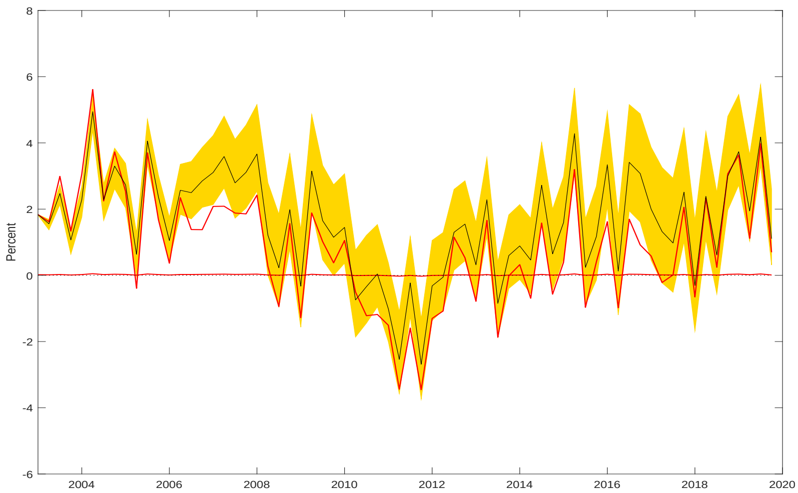


Figure 8 plots the counterfactual time series for native wage growth set to zero. The red line plots the observed data series for aggregate wage growth and the shaded region shows the area between the 16% and 84% quantiles of the counterfactual posterior distribution with the median plotted in a darker shade. The distribution is mostly above the data over the sample period, illustrating that the absence of the immigration shock implies a higher rate of native wage growth in the counterfactual.

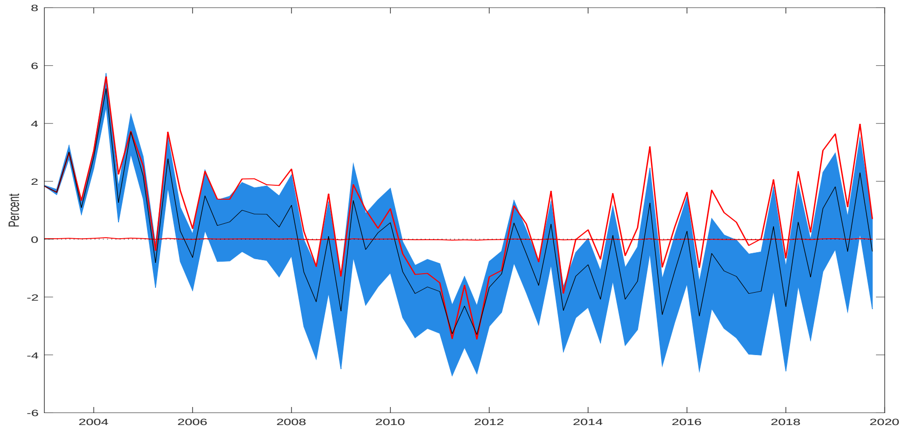
Figure 8 plots the counterfactual time series for aggregate native wages with the migration shock set to zero. The median and the 16% and 84% quantile bands of the counterfactual are colored yellow and the actual time series is colored red. As the yellow band is generally above the actual series, this shows that aggregate native wage growth is positively impacted by the absence of the migration shock particularly in time periods before the financial crisis and in the period before Brexit. This is consistent with the historical decomposition displayed in Figure 6 where these periods were those with the strongest negative effects of the migration shock. The total contribution of the migration shock also depends on its contribution to 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.[23]

Figure 9 plots the equivalent counterfactual time series with a) the demand shocks and b) the supply shocks set to zero. The demand shock has a persistently positive effect on native wage growth while the supply shock 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 shock has significant effects which cancel out over time, consistent with the historical decompositions in Figure 6 and 7.

[23] The Figure shows a positive effects of the absence of the immigration (yellow) shock.

Figure 9: Counterfactuals for aggregate native wage growth

(a) Counterfactual with no demand/business cycle shock



(b) Counterfactual with no supply shock

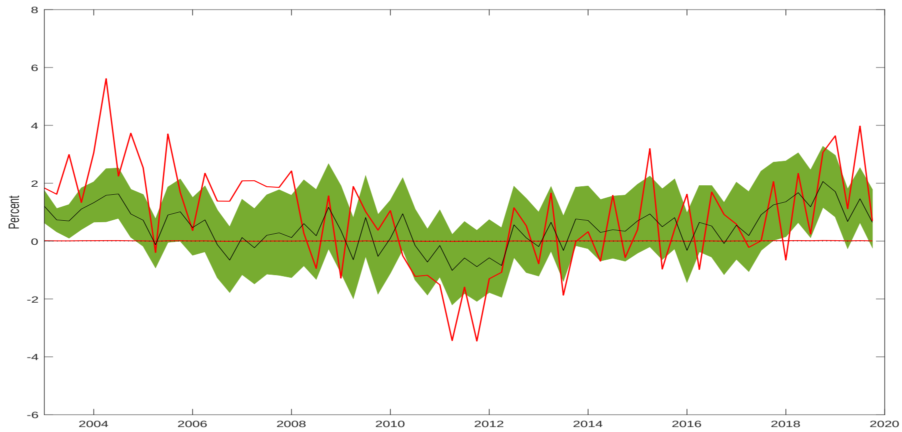


Figure 9 plots the counterfactual time series for native wage growth where in panel a) demand/business cycle shocks and panel b) supply (green) shocks, are set to zero. The red line plots the data series for aggregate native wage growth and the shaded region being the area between the 16% and 84% quantiles of the counterfactual posterior distribution with the median plotted in a darker shade. The distribution for the absence of the demand/business cycle shock is mostly below the data over the sample period, illustrating that the absence of the demand/business cycle shock 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 5.

Tables 2 and 3 display the growth of native wages and migration respectively over the sample period for all 35 sectors along with the median of the counterfactual series omitting one of the three aggregate shocks. These tables allow us to gauge the size of the effects described in Figures 8 and 9 and also show the heterogeneity of effects across sectors.

The first column of Table 2 displays the growth of median real native wages in the data. This shows over the sample period 2003-2019 real native wage growth was very small in many sectors. 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. [24]

The second column of Table 2 displays the counterfactual growth of native real wages where the immigration shock is set to zero. This column highlights in bold notable sectors where the difference in the native wage growth between the counterfactual and the observed time series was over 20%. The unskilled manual group has the most sectors with a 20% or greater difference. There are large differences are in food and hospitality, retail and transport, but also in sectors with large public employment, education and health. In almost all unskilled manual sectors, the counterfactual native wage was higher than the observed native wage, with the sole exception being the public administration sector. For the professional grouping, native wage growth in some sectors is worse in the counterfactual. These are the education, other services, production and scientific sectors. This is consistent with immigrant labor in these sectors being complementary to domestic labor. Five professional sectors show large positive differences. These are the construction, media, 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/business cycle shock 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/business cycle shocks. The counterfactuals for the absence of supply shocks are listed in the fourth column. These are weaker effects than the other two which is consistent with Figure 9b since, as we have seen, the effects of the supply shock 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 2 that the migration share grew across all sectors over the sample period, although with substantial heterogeneity across sectors. When the migration shock 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 shocks. The scale of the reduction in migration share varies a lot across sectors. Indeed in the public administration sector, the

[24] This is broadly consistent with other data such as the ONS monthly wages and salaries survey, available at https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes /bulletins/averageweeklyearningsingreatbritain/january2025

migrant share grows when the aggregate migration shock is set to zero. While the results 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. Columns three and four shows the absence of demand and supply shocks reduces growth in the migrant share, and as before these aggregate shocks manifest themselves differently across sectors.

Table 2

Cumulative native wage growth 2003-2019 by sector in the data and under counterfactuals setting aggregate shocks to zero

Sector	**Native wage growth in data**	**Counterfactual Migration Shock**	**Counterfactual Demand Shock**	**Counterfactual Supply Shock**
Professional sectors				
Production	0.99	0.98	0.88	0.94
Construction	1.05	**1.32**	0.87	0.95
Retail	0.98	**1.28**	0.90	0.96
Media&IT	0.93	1.16	0.76	0.94
Finance	0.98	1.03	0.73	0.91
Scientific	0.99	0.93	0.98	0.90
Transport&Support Services	1.05	**1.34**	0.80	1.02
Public Admin	1.00	**1.27**	0.72	0.92
Education	0.91	0.88	0.89	0.83
Health	1.05	1.05	1.00	0.95
OtherServices	1.08	0.86	1.16	0.94
Other non-manual sectors				
Production	1.11	1.25	1.04	1.11
Retail	1.04	1.09	0.91	0.98
Media&IT	1.03	0.96	1.01	1.01
Finance	1.21	**1.55**	1.14	1.21
Scientific	1.00	0.75	1.27	0.92
Transport&Support Services	1.13	**1.53**	0.92	1.10
Public Admin	1.08	1.19	1.11	1.01
Education	1.07	0.99	0.88	0.98
Health	1.06	1.17	0.88	0.96
OtherServices	1.11	**1.53**	0.81	1.04
Skilled manual sectors				
Production	1.10	**1.30**	**0.83**	1.03
Construction	1.11	**1.33**	**0.88**	1.05
Transport&Support Services	1.04	1.09	**0.75**	1.01
Public Admin	1.15	1.26	1.01	1.06
Unskilled manual sectors				
Production	1.13	1.32	0.86	1.07
Construction	1.13	1.18	0.77	1.03
Retail	1.22	**1.55**	0.83	1.17
Food&Hospitality	1.23	**1.44**	1.08	1.14
Finance	1.08	**1.45**	0.79	1.07
Transport&Support Services	1.14	1.32	0.97	1.06
Public Admin	1.19	1.17	1.34	1.10
Education	1.12	**1.37**	0.89	1.05
Health	1.13	1.32	0.89	1.07
OtherServices	1.18	**1.44**	0.81	1.12
Aggregate wage growth	1.16	1.31	0.96	1.08

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 fundamental shocks 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 aggregate shocks to zero

Sector	**Migration Share Growth in data**	**Counterfactual Migration Shock**	**Counterfactual Demand Shock**	**Counterfactual Supply Shock**
Professional Sectors				
Production	1.79	1.79	**0.67**	1.73
Construction	1.61	1.58	1.48	1.80
Retail	1.50	**1.11**	1.27	1.52
Media&IT	1.48	**0.69**	1.65	1.49
Finance	1.48	**0.89**	**1.96**	1.55
Scientific	1.60	**0.94**	1.66	1.55
Transport&Support Services	1.39	**1.14**	**0.94**	1.37
Public Admin	1.34	**3.38**	**0.53**	1.26
Education	1.45	1.26	1.87	1.50
Health	1.32	1.30	1.03	1.28
OtherServices	1.24	0.77	1.78	1.32
Other Non-Manual Sectors				
Production	1.81	**0.28**	**6.90**	1.72
Retail	1.70	1.67	1.86	1.74
Media&IT	1.27	1.15	0.99	1.18
Finance	1.79	1.60	1.63	1.63
Scientific	2.10	**1.32**	**1.66**	1.85
Transport&Support Services	1.39	1.26	**1.03**	1.11
Public Admin	1.03	**0.50**	1.16	0.84
Education	1.13	0.83	1.15	1.02
Health	1.47	**2.11**	1.50	1.46
OtherServices	1.41	1.34	1.18	1.51
Skilled Manual Sectors				
Production	2.27	2.80	**1.39**	1.86
Construction	2.14	**0.60**	1.75	1.60
Transport&Support Services	1.73	**1.02**	**2.24**	1.61
Public Admin	1.13	**0.26**	1.07	0.85
Unskilled Manual Sectors				
Production	2.83	**0.79**	2.89	2.27
Construction	2.28	**0.55**	2.53	2.57
Retail	2.45	**1.64**	**1.73**	2.27
Food&Hospitality	1.72	1.73	**0.88**	1.50
Finance	2.13	2.41	1.86	1.80
Transport&Support Services	2.72	**1.69**	2.40	2.23
Public Admin	1.63	**5.53**	**0.89**	1.54
Education	1.94	1.59	1.63	1.89
Health	2.45	1.49	2.41	1.94
OtherServices	1.53	1.08	**0.85**	1.50
Aggregate Migration Share Growth	2.03	1.30	1.94	1.88

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 fundamental shocks 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.

Figure 10: Impulse responses for the unskilled manual sectors using the sign restriction approach

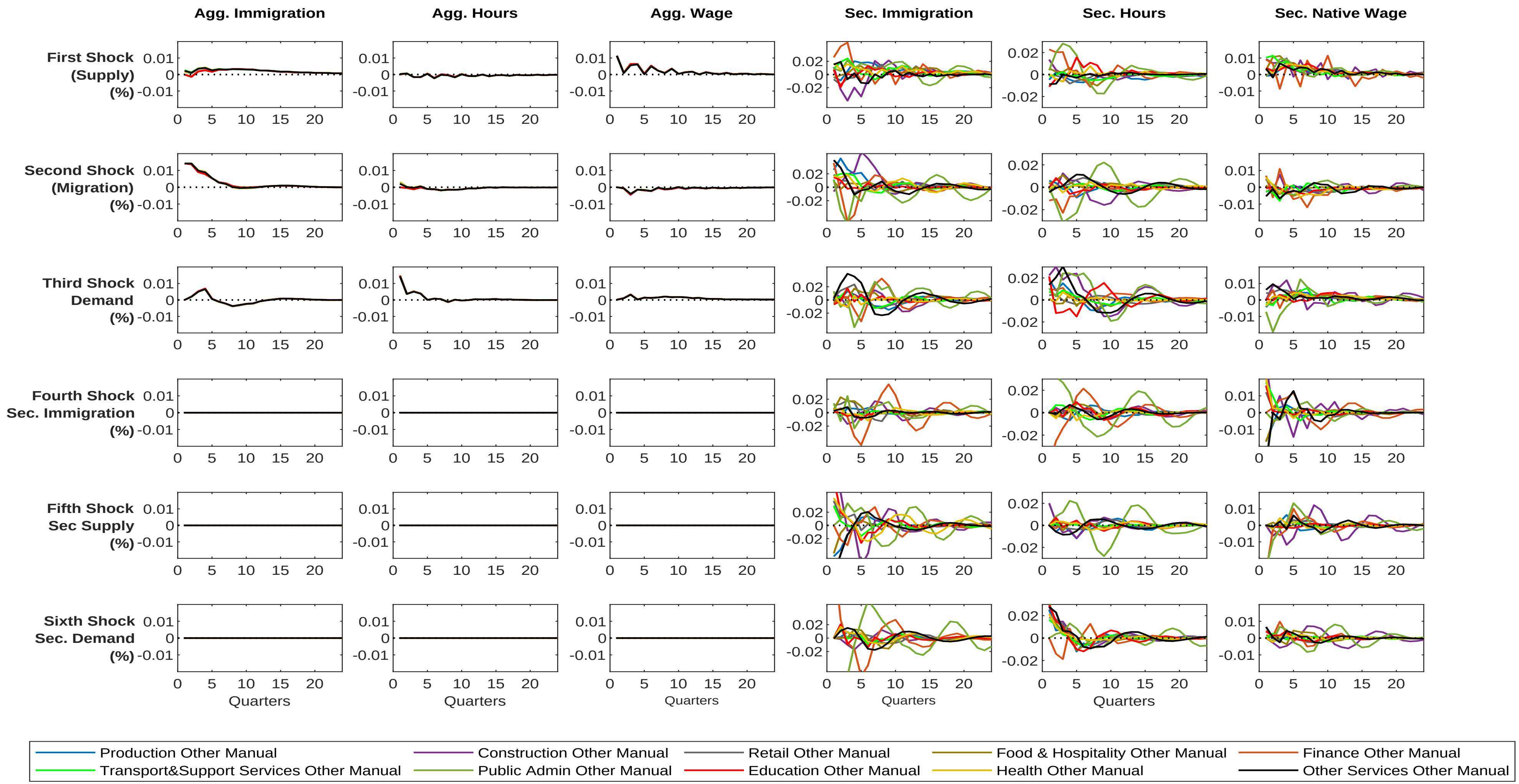


Figure 10 plots the median impulse responses for the unskilled manual sectors using the sign restriction approach of section 4.1.2. Each row plots the responses to a particular shock (row 1 is the first identified shocks, aggregate migration/ supply row 2 is the second identified shock, aggregate supply/migration, 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 and appear for the most part to be a thick line.

5.2 Results for sectoral variables

We now focus on the extent of sectoral variation in the impact of these shocks. Figure 10 plots the median impulse responses from the 10 VARs estimated for the 10 unskilled manual sectors in the dataset.[25] 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 of each other, this similarity demonstrates the accuracy of the estimation process. The restrictions, described in section 4, 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 10. Thus the top left 3×3 submatrix of Figure 10 is close to the responses of an independent 3 dimensional VAR in the aggregate variables. These responses were discussed in Figure 5 in section 5.1 above.

The top right 3×3 submatrix of Figure 10 shows the responses of the sectoral variables to the same aggregate shocks. These submatrices show the very different reactions across sectors to aggregate shocks with for example some sectors experiencing an increase in sectoral migration share in response to an aggregate migration shock and others a decrease. 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.

While the top right 3×3 submatrix Figure 10 shows the importance of macroeconomic shocks to the sectoral labor markets, the bottom right 3×3 submatrix shows the effects of sectoral shocks. 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 health professional and unskilled construction sectors, which have both experienced large increases in immigration.[26] These are displayed in Figure 11.

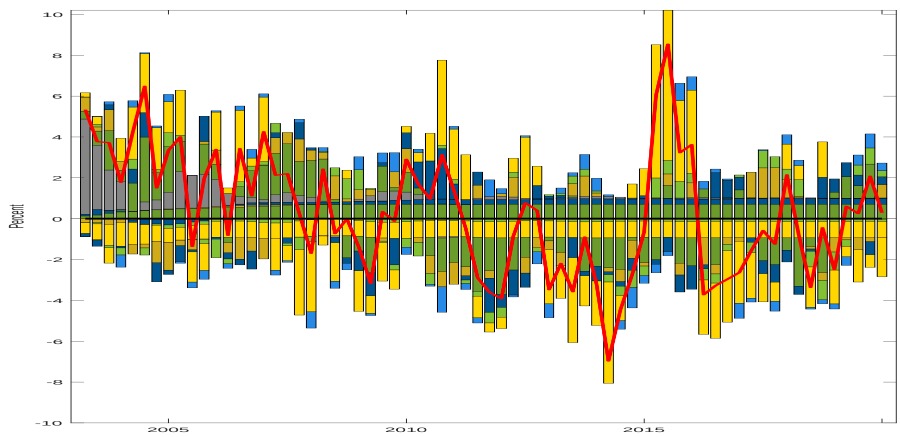
Historical decompositions at the sectoral level have eight different contributing factors, the three aggregate and sectoral shocks together with the constant and initial conditions. As in Figure 7 we have also decomposed the constant effects into parts associated with

[25] The impulse responses for the other sectors are available on request and those for the Cholesky approach are displayed in Appendix B.
[26] We place the historical decompositions of sectoral wage growth for all 35 sectors in Appendix D

their fundamental shocks. We have used the same color for the sectoral shocks as their corresponding aggregate shocks but have chosen a lighter shade of these colors for the sectoral shocks in order to differentiate them from the aggregate shocks.

Figure 11: Historical decomposition of native wages in health professional and unskilled construction sectors

(a) Health professional sector



(b) Unskilled manual construction sector

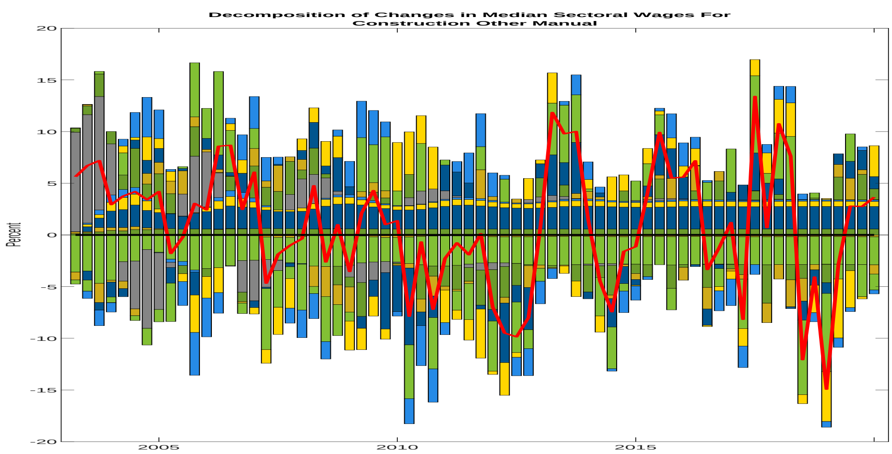


Figure 11 plots the median estimate of the historical contribution of each shock on native wage growth in the health professional and unskilled manual construction sectors. In each panel the red line plots sectoral native wage growth.

Figure 11a for the health professional sector shows the large role played by sectoral supply shocks which are colored light yellow. As detailed in Table 2 aggregate shocks play only a very small role in wages in this sector. The historical decomposition bears this out. The large effects of the sectoral supply shock is true both for the variation and also the long run effects via the constant which is negative. The positive constant effect is associated with the aggregate, green, supply shock. Note that, the interpretation of the sectoral historical decompositions are less straightforward because one cannot assume, for example, that an aggregate supply shock has a negative correlation with sectoral migration as they do on aggregate because of the heterogeneity in sectoral impulse responses. However for the professional health sector this is the case.[27]

Figure 11b for the decomposition of native wage growth in the unskilled construction sector, shows that aggregate immigration shocks, (dark yellow) play a very small role in native wage growth, which is consistent with Table 2. The dominant shocks for this series are the sectoral supply shocks (green) for both variation over time and wage growth, while aggregate demand (dark blue) has a noticeable positive role on long run wage growth via the constant term.

Taken together these figures illustrate how the contribution of aggregate and sectoral demand, supply and migration shocks to native wage growth differs across sectors. We have focused here on the historical decompositions of wage growth in the health professional and unskilled construction sectors as the impulses for these sectors are quite clear. In other sectors the effects are less strong but as we have shown in Table 2 there are many sectors where the cumulative contribution of the aggregate migration shock is substantially negative.[28]

[27] These impulses for the professional health sector to aggregate and sectoral supply and demand shocks are displayed in Figure B4 in the Appendix B.

[28] Decompositions based on the other methods are available on request.

6 Conclusion

We asked at the outset whether immigration could be thought of as an exogenous shock, whether immigration can be plausibly associated with adverse labor market effects, and if so, whether these effects are similar across different sectors of the economy. We have applied established methods of multiple time series analysis to decompose a time series of UK labor market variables into 'fundamental' constituent parts. As argued by Uhlig (2005) and Baumeister and Hamilton (2015), economic theory does not provide sufficient information to definitively identify these fundamental parts. We have therefore applied two different, though plausible, approaches for characterizing them, across 35 different sectors of the UK labor market. We have found in both identification schemes that aggregate immigration is, in part, determined by shocks that could be considered aggregate supply and aggregate demand shocks. Thus what have previously been considered the effects of exogenous shocks to immigration may in fact be the result of multiple underlying causes that sometimes work in opposing directions.

In answer to the question of whether there are adverse labor market effects of immigration, in each identification approach we have found that there are shocks where immigration and native wages are positively associated, and shocks where immigration and native wages are negatively associated. A natural interpretation for the positive association at the aggregate level is a macroeconomic demand or business cycle shock. One interpretation of the negative association is that migration is causing, directly or indirectly, a reduction in native wages. We have shown that this shock accounts for most of the variation in migration and plays a significant role in the determination of native wage growth and that the size of its effect can vary considerably across sectors.

The literature on the labor market effects of immigration has frequently noted that its results are subject to the proviso that they are abstracting away from the effects of demand shocks and sectoral heterogeneities. Our approach has shown that this proviso is indeed justified and that the literature may not be identifying significant adverse effects of immigration on native wages, particularly in certain sectors, because over the same period demand shocks have been working in the opposite direction. Our conclusion therefore echoes that of Uhlig (2005) regarding monetary policy. It is that there are good reasons for being uncertain about the labor market effects of immigration.

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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.

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

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 (3) in the text.

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

$$\begin{aligned} \widehat{Y_t} =& \widehat{C} + F\widehat{C} + F^2\widehat{C} + \cdots + \widehat{u_t} + F\widehat{u_{t-1}} + F^2\widehat{u_{t-2}} + \cdots + \\ \widehat{Y_t} =& \widehat{\mu} + \Psi(L)\widehat{u_t} \end{aligned} \tag{A4}$$

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 (1) 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

B.1 Figures for the Cholesky Identification Approach

In the text we presented results using the sign restriction methodology described in section 4.1.2. We also estimate the model using the Cholesky identifications approach and we present these results here. Responses of the aggregate variables to aggregate shocks are displayed in Figure B1 which is the counterpart of Figure 5. The responses in Figure B1 are extremely similar to those in Figure 5 but in a different order. The similarity of the shocks is not so surprising when one notes that the signs of the impulses of the Cholesky factor approach have a very similar pattern to those imposed by the sign restrictions. One only needs to replace the zero restrictions of the Cholesky factor with small, positive or negative, epsilon perturbation for them to have the same signs as those described in equation (6). Although similar, the sign restriction impulses do give a slightly larger role for the yellow colored shocks.

The historical decompositions using the Cholesky approach are displayed in Figure B2 which is the counterpart of Figure 7 for the sign restrictions approach. Again for aggregate variables the responses are very similar, although again the sign restriction impulses do give a slightly larger role for the migration shocks, colored yellow, than the Cholesky approach.

The results for the counterfactual exercise using the Cholesky approach are given in Tables B1 and B2 for wages and migration share respectively. They show a very similar pattern to their sign restriction counterparts in Tables 2 and 3 although the size of the contribution of the migration shock to wages is lower e.g in the unskilled manual sector there are now several sectors with wage rates 15% higher at the end of the sample when the migration shock is excluded compared to 20 % higher or more in the sign restriction case.

The impulse response for the sectoral variable are displayed Figure B3 which is the counterpart of Figure 10. Again for aggregate variables the responses are very similar, although ordered differently while for the sectoral variables in the Cholesky case the strongest responses are on the diagonals, which naturally leads one to think of the fourth ordered shock as a sectoral migration shock and the fifth and sixth ordered shocks as sectoral hours and sectoral wage shocks respectively.

Figure B1: Impulse responses of aggregate variables to aggregate shocks - Cholesky approach

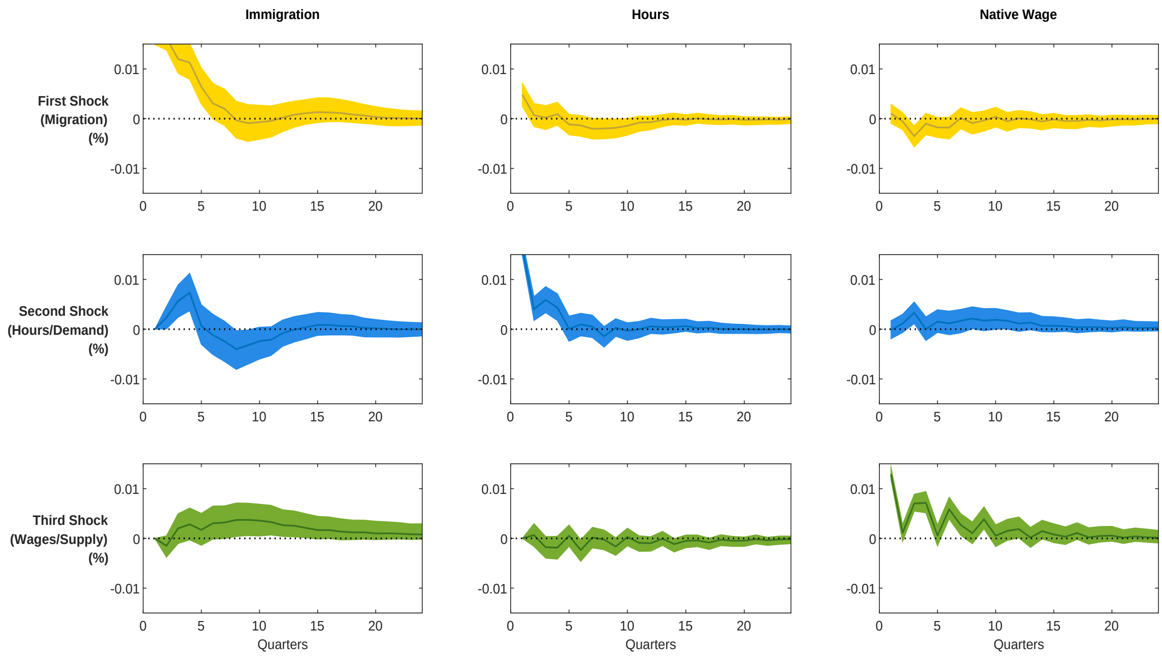
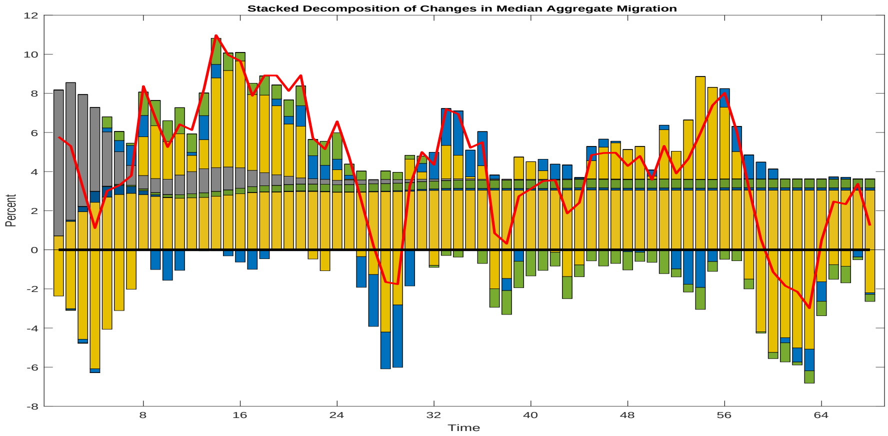


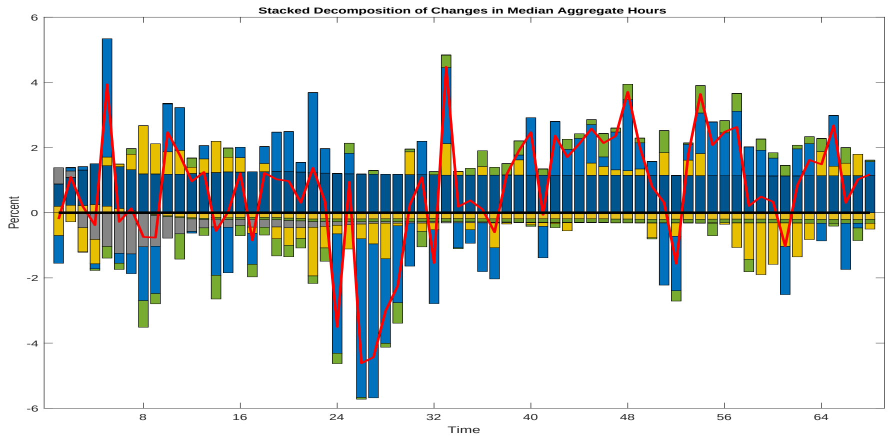
Figure B1 plots the impulse responses of the aggregate variables to aggregate shocks for the unskilled manual sectors using the Cholesky factorization approach The impulses are colored to match those of similar shocks in the sign restriction approach in Figure 5. Thus the first shock in is colored yellow, the second shock, blue and the third shock, green. The shaded region is the area between the 16% and 84% quantiles of the posterior distribution with the median colored in a darker shade. .

Figure B2: Historical decomposition of aggregate variables including constant decomposition-Cholesky approach

(a) Aggregate migration



(b) Aggregate hours



(c) Aggregate native wages

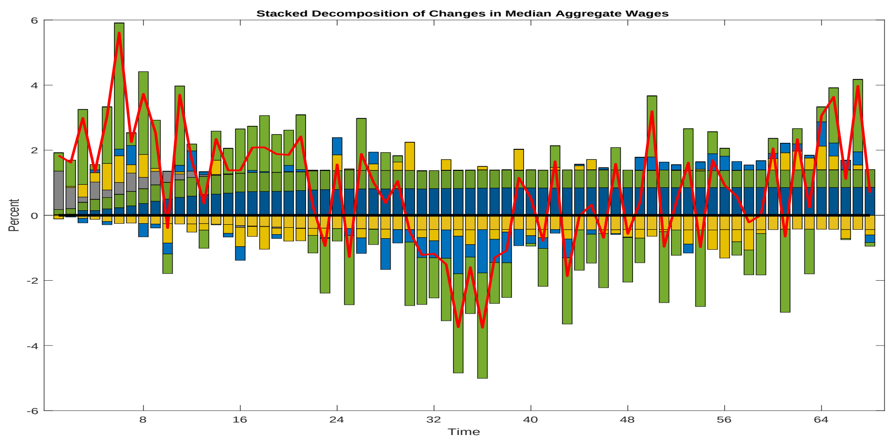


Figure B2 plots the same historical decompositions as Figure 7 for the sign restrictions approach, but where the Cholesky identification approach is used. The decompositions are taken from the unskilled transport services sector. In each panel the red line plots data for aggregate native wage growth. The colors of the bars relate to the shocks in Figure B1.

Table B1

Cumulative native wage growth 2003-2019 by sector in the data and under counterfactuals setting aggregate shocks to zero

Sector	**Native wage growth in data**	**Counterfactual 1st Cholesky**	**Counterfactual 2nd Cholesky**	**Counterfactual 3rd Cholesky**
Professional sectors				
Production	0.99	0.94	0.94	0.95
Construction	1.05	**1.24**	0.92	0.96
Retail	0.98	**1.23**	0.93	0.97
Media&IT	0.93	1.06	0.81	0.93
Finance	0.98	0.93	0.80	0.92
Scientific	0.99	0.86	0.92	0.92
Transport&Support Services	1.05	1.23	0.84	1.01
Public Admin	1.00	1.11	0.83	0.95
Education	0.91	0.86	0.91	0.85
Health	1.05	1.02	1.04	0.98
OtherServices	1.08	0.84	1.18	0.99
Other non-manual sectors				
Production	1.11	1.21	1.05	1.11
Retail	1.04	1.10	0.93	1.00
Media&IT	1.03	0.93	1.06	0.98
Finance	1.21	**1.49**	1.18	1.19
Scientific	1.00	0.74	1.19	0.94
Transport&Support Services	1.13	**1.39**	0.85	1.14
Public Admin	1.08	1.15	1.12	1.03
Education	1.07	0.85	1.07	0.99
Health	1.06	1.03	0.92	0.99
OtherServices	1.11	**1.37**	0.87	1.07
Skilled manual sectors				
Production	1.10	1.20	0.90	1.05
Construction	1.11	1.22	0.94	1.03
Transport&Support Services	1.04	1.01	0.80	1.01
Public Admin	1.15	1.27	1.05	1.10
Unskilled manual sectors				
Production	1.13	1.20	0.94	1.08
Construction	1.13	1.08	0.86	1.05
Retail	1.22	**1.39**	0.91	1.18
Food&Hospitality	1.23	**1.39**	1.09	1.16
Finance	1.08	**1.38**	0.87	1.07
Transport&Support Services	1.14	1.24	0.98	1.06
Public Admin	1.19	1.15	1.38	1.11
Education	1.12	**1.27**	0.96	1.05
Health	1.13	1.26	0.93	1.08
OtherServices	1.18	1.32	0.89	1.14
Aggregate wage growth	1.155	1.33	0.95	1.07

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

Table B2

Cumulative migration growth 2003-2019 by sector in the data and under counterfactuals setting aggregate shocks to zero

Sector	Migration Share Growth in Data	Counterfactual 1st Cholesky	Counterfactual 2nd Cholesky	Counterfactual 3rd Cholesky
Professional Sectors				
Production	1.79	1.43	**0.81**	1.77
Construction	1.61	1.56	1.70	1.75
Retail	1.50	**1.04**	1.36	1.58
Media&IT	1.48	**0.69**	1.62	1.48
Finance	1.48	**0.87**	1.87	1.54
Scientific	1.60	**0.91**	1.60	1.54
Transport&Support Services	1.39	**0.98**	1.16	1.35
Public Admin	1.34	**2.81**	**0.73**	1.30
Education	1.45	1.53	1.79	1.51
Health	1.32	1.16	1.10	1.28
OtherServices	1.24	0.79	1.50	1.27
Other Non-Manual Sectors				
Production	1.81	**0.43**	**4.93**	1.69
Retail	1.70	1.90	1.94	1.80
Media&IT	1.27	0.96	1.29	1.23
Finance	1.79	**1.25**	1.93	1.65
Scientific	2.10	**0.96**	1.92	1.87
Transport&Support Services	1.39	**1.17**	1.30	1.17
Public Admin	1.03	**0.35**	1.13	0.92
Education	1.13	0.88	1.19	1.08
Health	1.47	**1.91**	1.45	1.44
OtherServices	1.41	1.35	1.30	1.46
Skilled Manual Sectors				
Production	2.27	2.19	**1.72**	1.97
Construction	2.14	**0.60**	2.02	1.77
Transport&Support Services	1.73	**1.16**	2.06	1.63
Public Admin	1.13	**0.38**	1.18	0.94
Unskilled Manual Sectors				
Production	2.83	0.86	3.08	2.29
Construction	2.28	0.51	2.69	2.47
Retail	2.45	1.40	1.85	2.29
Food&Hospitality	1.72	1.42	1.13	1.60
Finance	2.13	2.51	1.70	1.88
Transport&Support Services	2.72	1.57	2.40	2.31
Public Admin	1.63	**4.07**	0.81	1.68
Education	1.94	1.44	1.56	1.92
Health	2.45	1.31	2.43	2.08
OtherServices	1.53	0.97	0.99	1.51
Aggregate Migration Share Growth	2.03	1.24	1.98	1.92

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

Figure B3: Impulse responses for the unskilled manual sectors using the Cholesky factor approach.

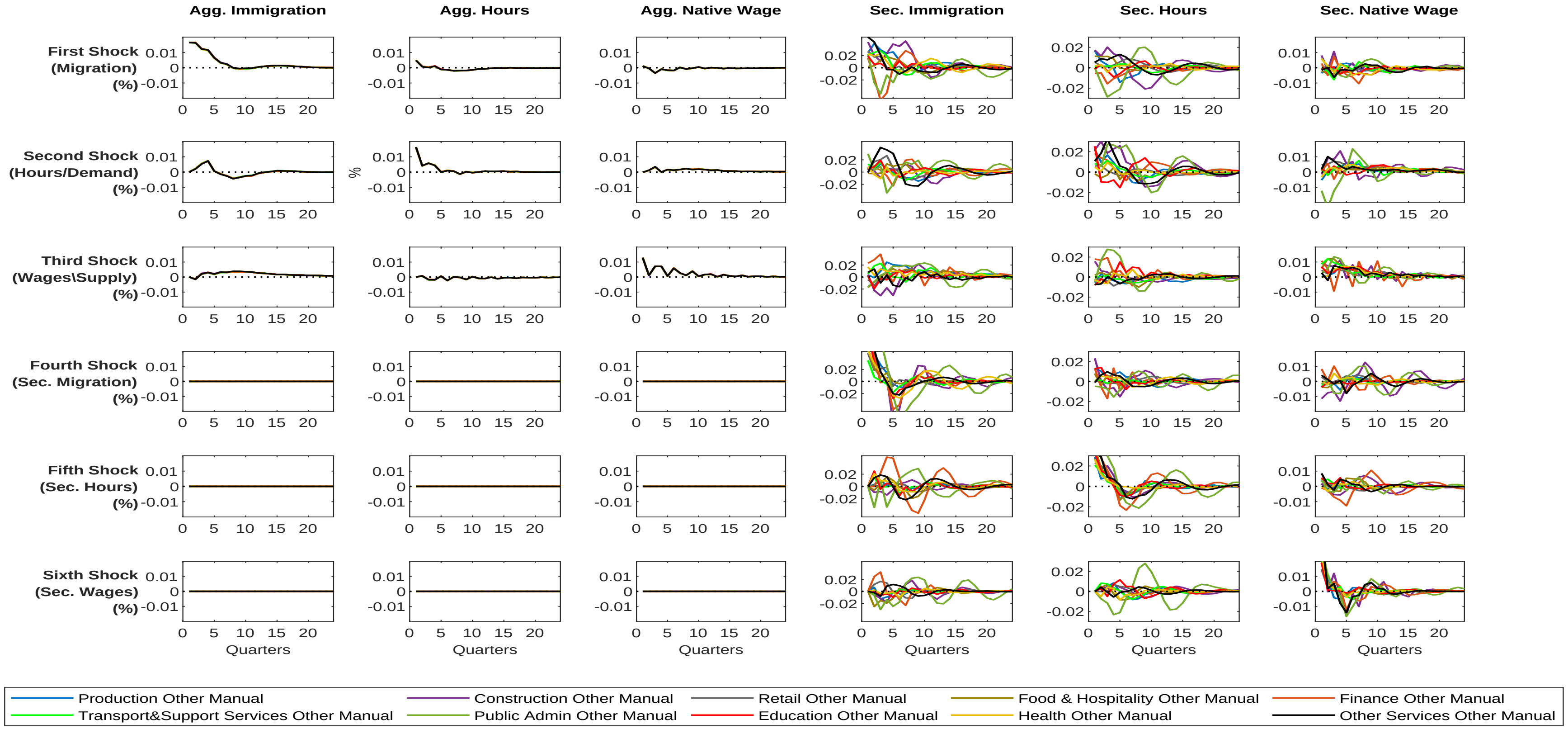


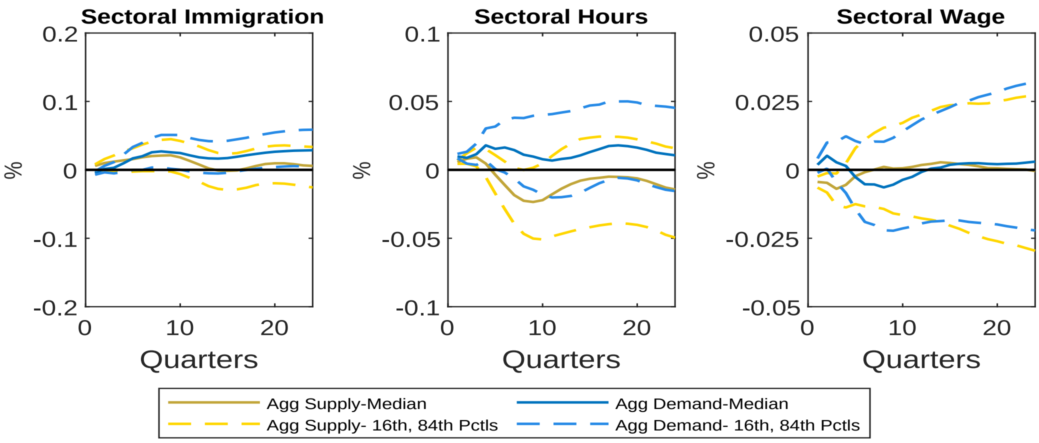
Figure B3 plots the median impulse responses for the unskilled manual sectors using the Cholesky factorization approach. Each row plots the responses to a particular shock (row 1 is the first shock, row 2 is the second shock, etc.) and each column is the responses of a particular variable (column 1 is 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 and appear for the most part to be a thick line.

B.2 Sectoral Impulses Responses

Figure B4 and Figure B5 plot median cumulative impulse responses, i.e. the levels - solid lines - as well as the 16th and 84th percentiles - dashed lines- of the sectoral variables to two aggregate and sectoral shocks for the health professional and unskilled construction sector. We choose to plot the cumulative responses as the non-cumulative responses sometimes oscillate which makes the longer run effects difficult to make out. In contrast the cumulative responses are clear. The responses to aggregate shocks are displayed in panel a) of each Figure and those to sectoral shocks in panel b). In both panels the shocks are identified using the sign restrictions approach, with the identified shocks corresponding to migration shocks colored yellow and those corresponding to aggregate demand/business cycle shocks colored blue. For the professional health sector, Figure B4, shows the strong negative association between wages and sectoral migration share and for unskilled construction sector, Figure B5, shows the strong positive effects of aggregate demand shocks on wages and negative association of sectoral migration.

Figure B4: Sectoral impulse responses in the health professional sector

(a) Aggregate shocks: sign restrictions



(b) Sectoral shocks: sign restrictions

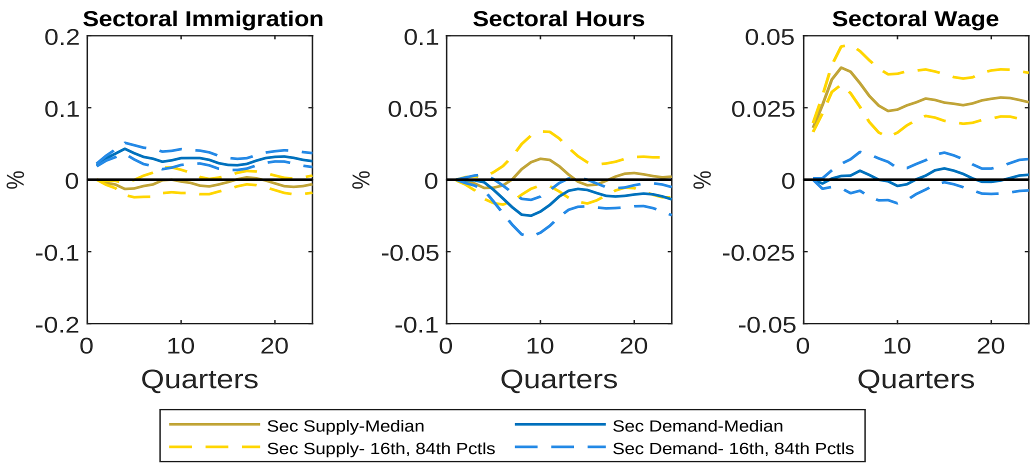
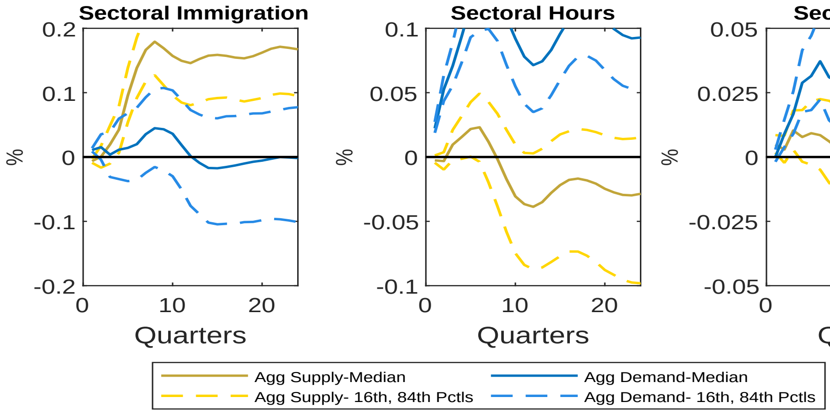
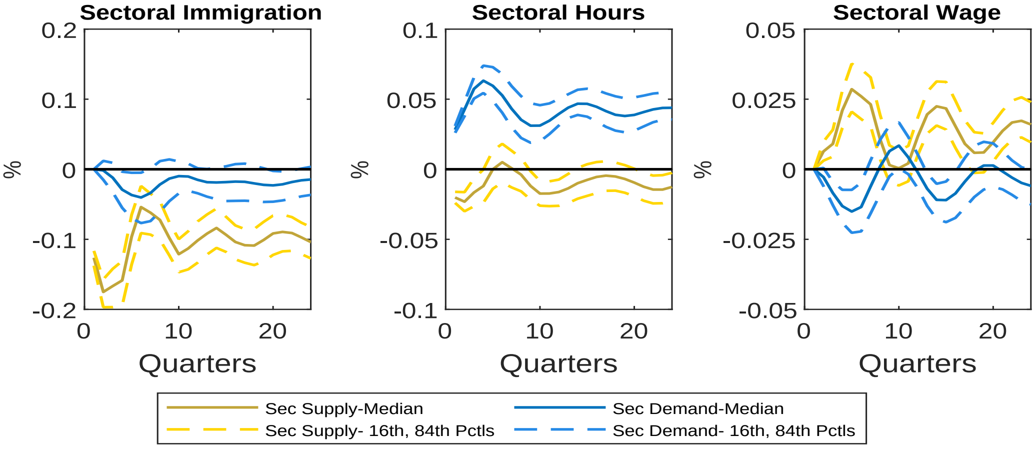


Figure B5: Sectoral impulse responses in the unskilled construction sector

(a) Aggregate shocks: sign restrictions



(b) Sectoral shocks: sign restrictions



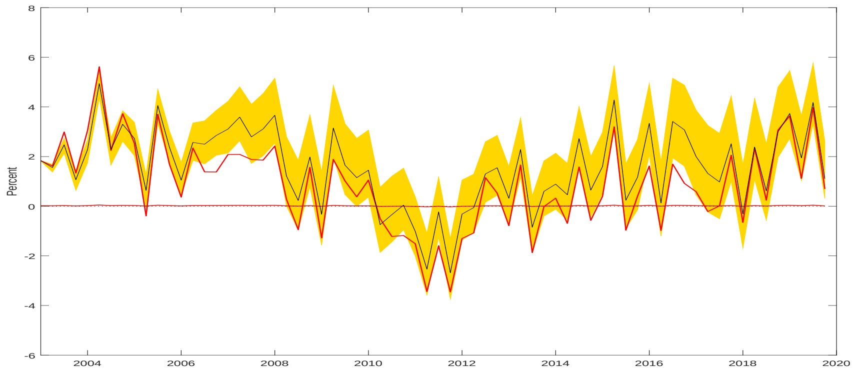
C Counterfactual Precision

The counterfactual exercizes are cumulative and so simulation variation is compounded. Therefore to check whether the results described in section 5.1.3 are robust to simulation variation we made 3 independent runs of our counterfactual exercize for the unskilled manual sectors, each with 80,000,000 draws from the posterior distribution, a burn in of 64,000,000 and a thinning factor of 4000 leaving a retained sample of 4000 draws. We present the aggregate wage counterfactual for the second identified shock in Figure C1. This shows that the counterfactual for aggregate wages is almost identical across the three runs. The counterfactual across the unskilled manual sectors is displayed in Table C3. This shows that the differences in the median counterfactual across runs is very small being at less than most 0.1 in most sectors.

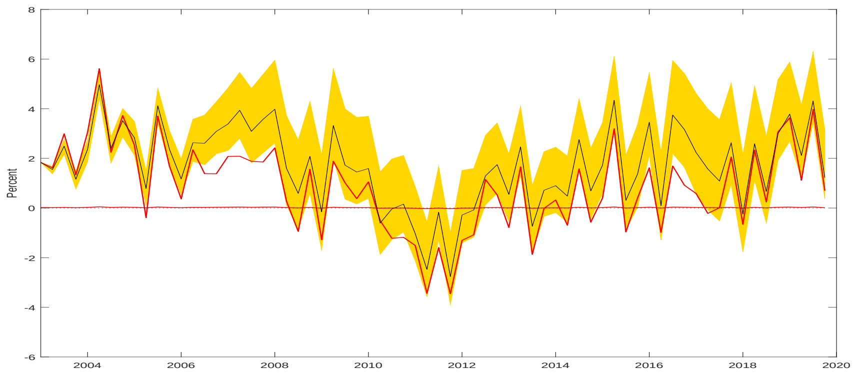
We also perform the same exercize for the Cholesky Approach. This samples directely from the posterior of the reduced form parameters and so needs fewer draws and is even less variable than the sign restriction approach. For this case we ran 3 independent runs of our counterfactual exercize for the unskilled manual sectors, each with 1,000,000 draws from the posterior distribution, a burn in of 250,000 and a thinning factor of 250 leaving a retained sample of 3000 draws. We present the aggregate wage counterfactual for the first cholesky shock in Figure C2. This shows again that the counterfactual for aggregate wages is almost identical across the three runs. The counterfactual across the unskilled manual sectors is displayed in Table C4 where again the differences in the median counterfactual across runs is very small being at most 0.02 and with most sectors less than this.

Figure C1: Counterfactuals for aggregate native wage growth where migration shocks set to zero

(a) Counterfactual run 1



(b) Counterfactual run 2



(c) Counterfactual run 3

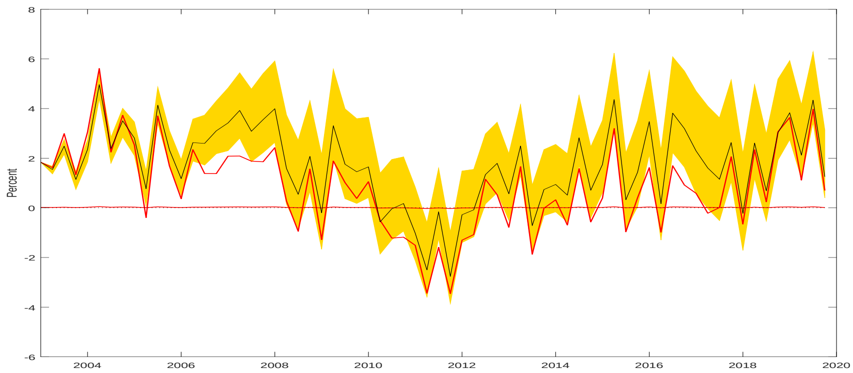
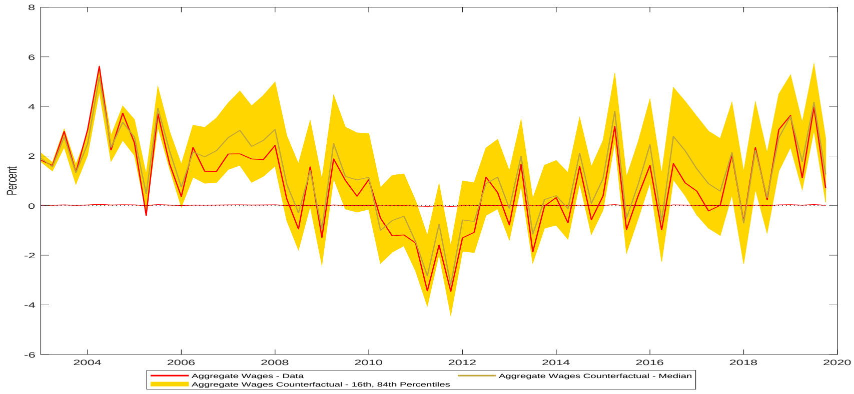


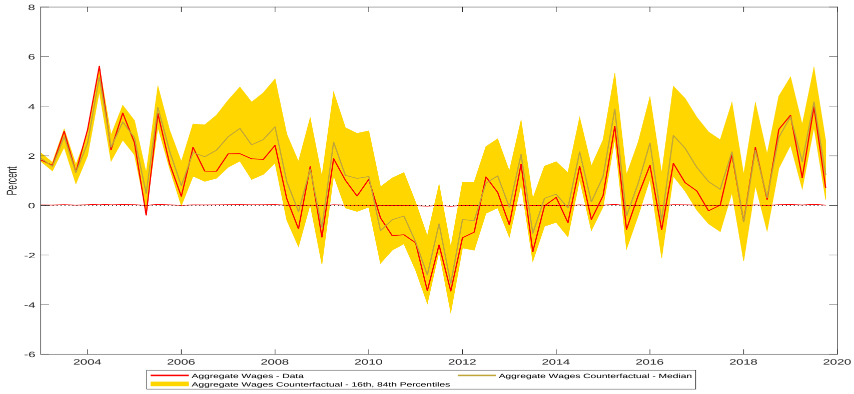
Figure C1 plots the counterfactual time series from three separate and independent runs for native wage growth where the second identified shock using sign restrictions , the migration shocks, is set to zero. The Figures for the three graphs are almost identical. In each case, the data is taken using the unskilled transport services VAR and the red line plots the data series for aggregate native wage growth and the shaded region being the area between the 16% and 84% quantiles of the counterfactual posterior distribution with the median plotted in a darker shade.

Figure C2: Counterfactuals for aggregate native wage growth where migration shocks set to zero using the Cholesky Approach

(a) Counterfactual run 1



(b) Counterfactual run 2



(c) Counterfactual run 3

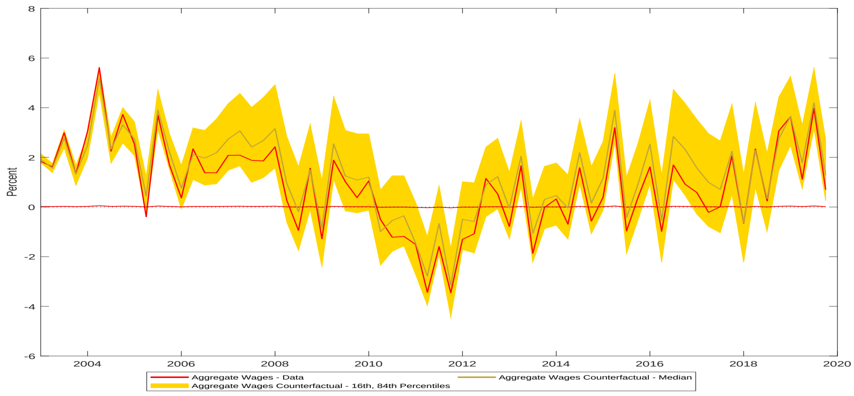


Figure C2 plots the counterfactual time series from three separate and independent runs for native wage growth where the first cholesky shock, the migration shocks, is set to zero. The Figures for the three graphs are almost identical. In each case, the data is taken using the unskilled transport services VAR and the red line plots the data series for aggregate native wage growth and the shaded region being the area between the 16% and 84% quantiles of the counterfactual posterior distribution with the median plotted in a darker shade.

Table C3

Variation across 3 runs of the sign restriction counterfactual for unskilled manual sectors

Sector	**Wage Growth in Data**	**Counterfactual Migration (yellow)**	**Counterfactual Demand (blue)**	**Counterfactual Supply (green)**
<u>**Unskilled Manual Sectors**</u>				
Production	1.13	1.31, 1.33, 1.35	0.86, 0.86, 0.86	1.07, 1.06, 1.05
Construction	1.13	1.18, 1.18, 1.17	0.77, 0.72, 0.77	1.03, 1.05, 1.03
Retail	1.22	1.55, 1.55, 1.57	0.83, 0.83, 0.84	1.17, 1.17, 1.16
Food&Hospitality	1.23	1.44, 1.45, 1.54	1.08, 1.05, 0.98	1.14, 1.15, 1.13
Finance	1.08	1.45, 1.41, 1.47	0.79, 0.83, 0.80	1.07, 1.08, 1.09
Transport&Support Services	1.14	1.32, 1.32, 1.34	0.97, 0.88, 0.92	1.06, 1.06, 1.05
Public Admin	1.19	1.17, 1.08, 1.14	1.34, 1.44, 1.42	1.10, 1.10, 1.10
Education	1.12	1.37, 1.39, 1.37	0.89, 0.87, 0.91	1.05, 1.03, 1.04
Health	1.13	1.32, 1.38, 1.31	0.89, 0.85, 0.89	1.07, 1.07, 1.08
OtherServices	1.18	1.44, 1.48, 1.50	0.81, 0.78 , 0.79	1.12, 1.12, 1.10
Aggregate Wage Growth	1.16	1.31, 1.32, 1.33	0.96, 0.96, 0.96	1.08, 1.07, 1.07

Notes: The table reports the cumulative wage growth 2003-2019 by sector in the data, and in the median of the counterfactual series using the sign restriction approach, derived by setting one of the aggregate fundamental shocks to zero, from three separate and independent runs of the sampler. The cumulative native wage growth is calculated as $\prod_{t=1}^{T}(1 + \text{native wage growth}_t)^{0.25}$.

Table C4

Variation across 3 runs of the Cholesky counterfactual for unskilled manual sectors

Sector	**Wage Growth in Data**	**Counterfactual 1st Cholesky**	**Counterfactual 2nd Cholesky**	**Counterfactual 3rd Cholesky**
<u>**Unskilled Manual Sectors**</u>				
Production	1.13	1.21, 1.20, 1.21	0.94, 0.95, 0.94	1.07, 1.08, 1.08
Construction	1.13	1.08, 1.10, 1.09	0.86, 0.85, 0.85	1.07, 1.05, 1.05
Retail	1.22	1.37, 1.38, 1.37	0.92, 0.92, 0.92	1.18, 1.19, 1.18
Food&Hospitality	1.23	1.38, 1.39, 1.39	1.11, 1.09, 1.10	1.15, 1.15, 1.15
Finance	1.08	1.38, 1.37, 1.38	0.87, 0.87, 0.87	1.07, 1.07, 1.07
Transport&Support Services	1.14	1.22, 1.24, 1.24	0.98, 0.98, 0.96	1.07, 1.07, 1.08
Public Admin	1.19	1.15, 1.15, 1.14	1.37, 1.37, 1.39	1.11, 1.11, 1.11
g	1.12	1.27, 1.26, 1.27	0.96, 0.96, 0.96	1.06, 1.06, 1.06
Health	1.13	1.27, 1.26, 1.25	0.92, 0.93, 0.93	1.08, 1.08, 1.09
OtherServices	1.18	1.33, 1.32, 1.32	0.89, 0.89 , 0.89	1.12, 1.13, 1.13
Aggregate Wage Growth	1.16	1.24, 1.24, 1.24	1.02, 1.02, 1.02	1.08, 1.08, 1.08

Notes: The table reports the cumulative wage growth 2003-2019 by sector in the data, and in the median of the counterfactual series using the cholesky approach, derived by setting one of the aggregate fundamental shocks to zero, from three separate and independent runs of the sampler. The cumulative native wage growth is calculated as $\prod_{t=1}^{T}(1 + \text{native wage growth}_t)^{0.25}$.

D Wage decompositions for all sectors

In Appendix D we plot the sectoral historical decompositions for native wages of all 35 estimated sectors. Those for unskilled manual sectors are given in Figure D1, those for skilled manual in Figure D2, those for the other non-manual sectors in Figure D3 and those for the professional sectors in Figure D4.

Figure D1: Historical Decompositions for native wages in the unskilled manual sectors using sign restriction.

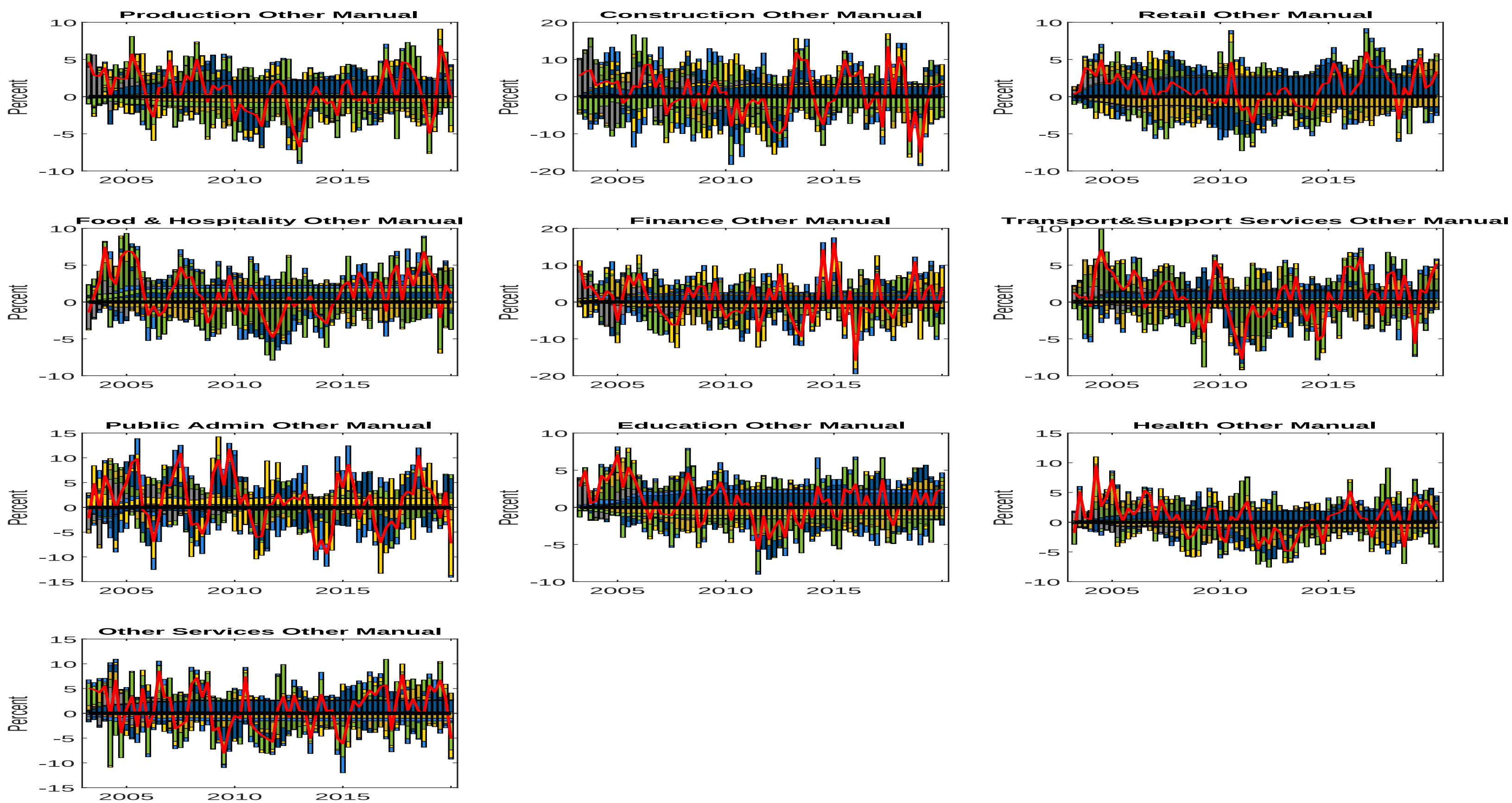


Figure D1 plots the median historical decompositions for native wage growth for all the unskilled manual sectors using the sign restrictions approach. These show the contribution of the six identified shocks and the constant term and initial conditions. In each panel the red line plots data for sectoral native wage growth. The colors of the bars relate to the colors of the impulses in Figure 5 with lighter shades for the sectoral shocks and darker for the aggregate shocks. Note interpretation of the sectroal shocks must be done with references to the sectoral impulse responses as discuussed in section 5.2.

Figure D2: Historical Decompositions for native wages in the skilled manual sectors using sign restriction.

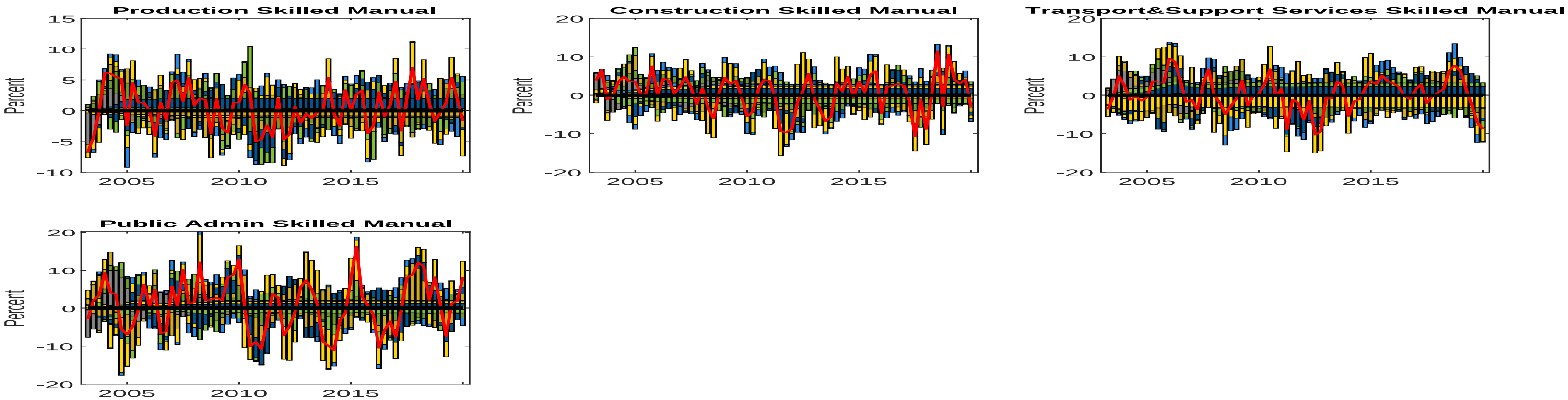


Figure D2 plots the median historical decompositions for native wage growth for all the skilled manual sectors using the sign restrictions approach. These show the contribution of the six identified shocks and the constant term and initial conditions. In each panel the red line plots data for sectoral native wage growth. The colors of the bars relate to the colors of the impulses in Figure 5 with lighter shades for the sectoral shocks and darker for the aggregate shocks. Note interpretation of the sectroal shocks must be done with references to the sectoral impulse responses as discuussed in section 5.2.

Figure D3: Historical Decompositions for native wages in the other non-manual sectors using sign restriction.

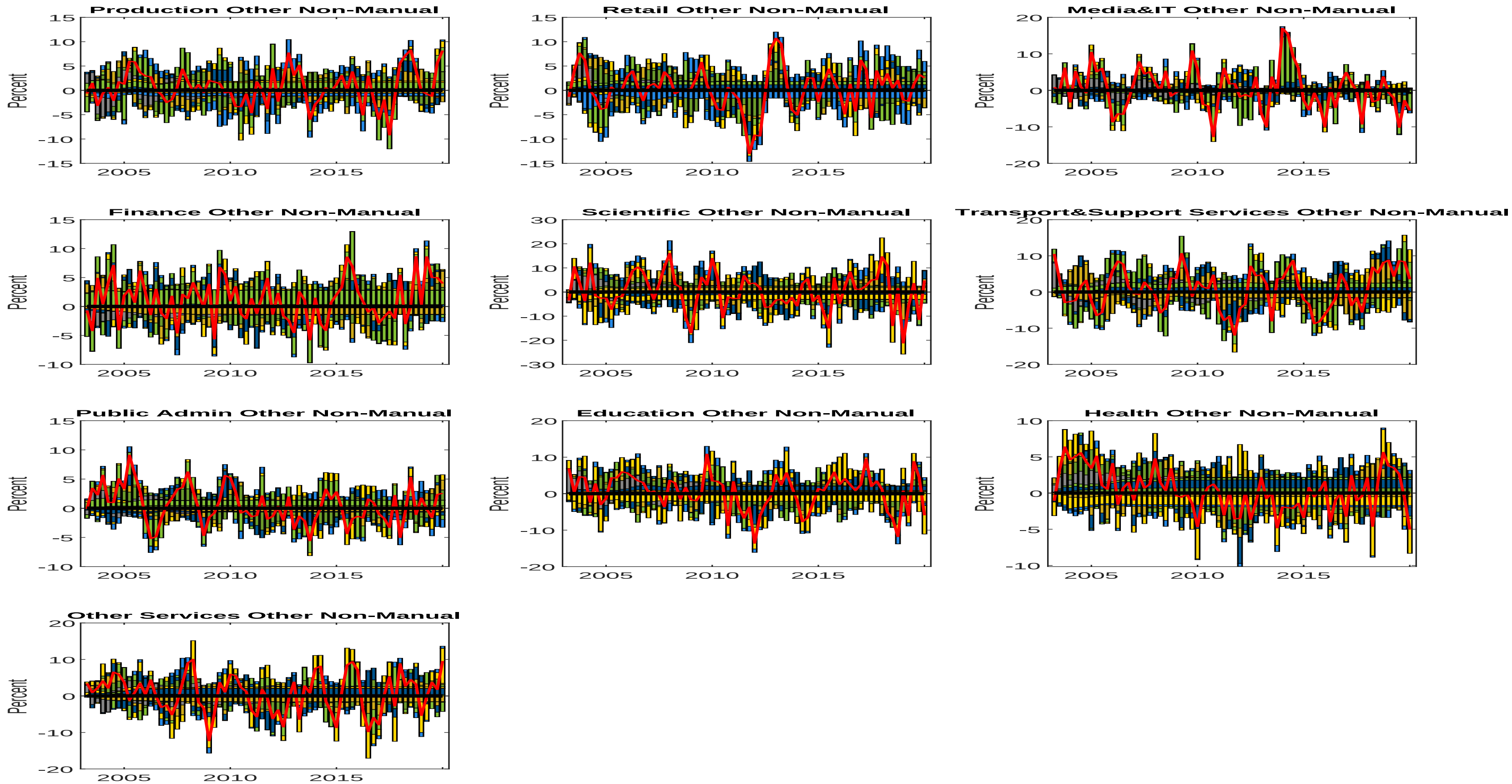


Figure D3 plots the median historical decompositions for native wage growth for all the other non-manual sectors using the sign restrictions approach. These show the contribution of the six identified shocks and the constant term and initial conditions. In each panel the red line plots data for sectoral native wage growth. The colors of the bars relate to the colors of the impulses in Figure 5 with lighter shades for the sectoral shocks and darker for the aggregate shocks. Note interpretation of the sectoral shocks must be done with references to the sectoral impulse responses as discussed in section 5.2.

Figure D4: Historical Decompositions for native wages in the Professional sectors using sign restriction.

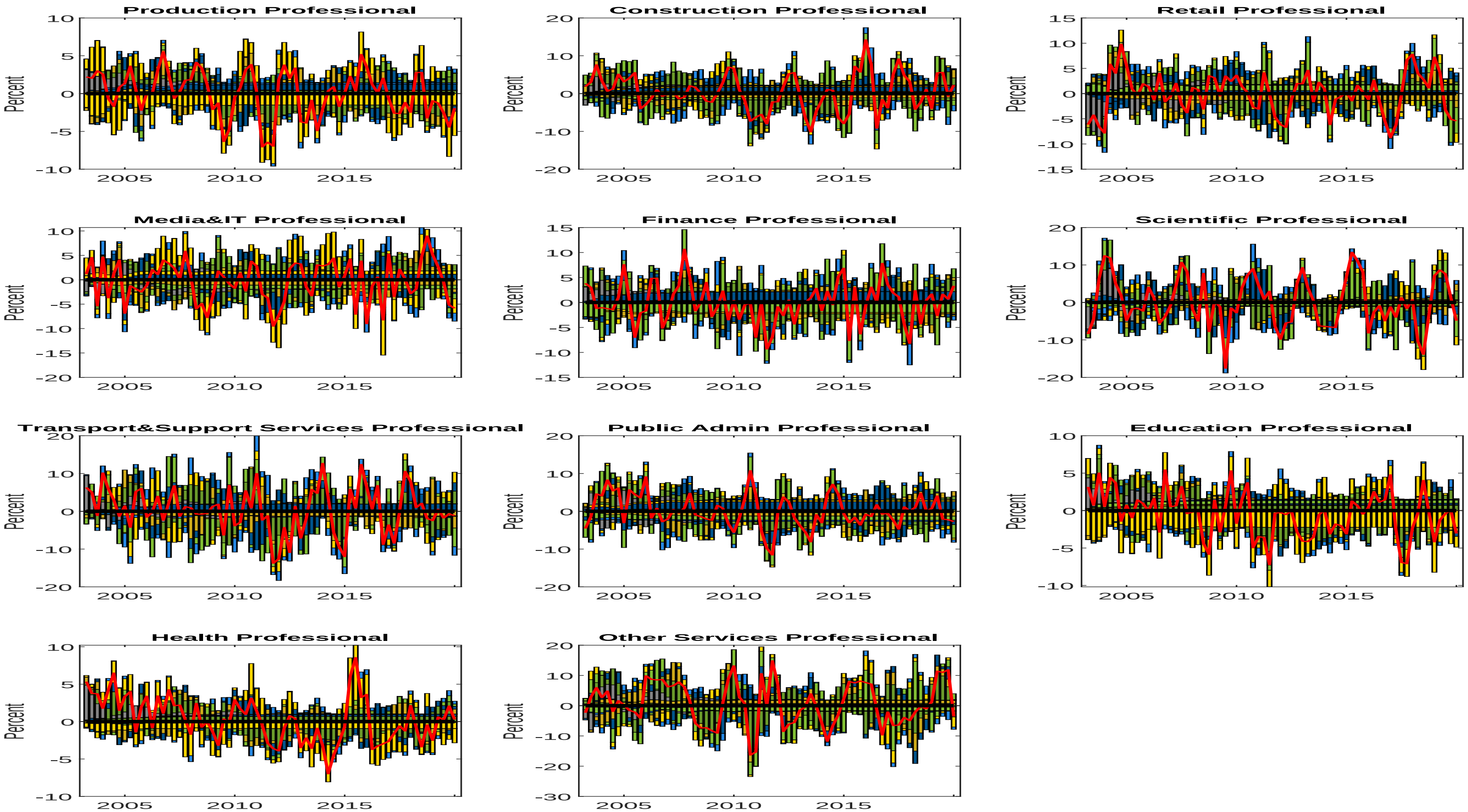


Figure D4 plots the median historical decompositions for native wage growth for all the professional sectors using the sign restrictions approach. These show the contribution of the six identified shocks and the constant term and initial conditions. In each panel the red line plots data for sectoral native wage growth. The colors of the bars relate to the colors of the impulses in Figure 5 with lighter shades for the sectoral shocks and darker for the aggregate shocks. Note interpretation of the sectoral shocks must be done with references to the sectoral impulse responses as discussed in section 5.2.