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Occupational shortage and labor market adjustments: A theory of islands

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Abstract

Human Resources officers report occupational shortage to be the main cause of unfilled vacancies. Yet, it is not clear whether these are empty complaints or actually lead to effective wage and employment adjustments over time. By crossing data from the UK Employer Skill Survey with the UK Labor Force Survey, we show that shortage only leads to wage and employment adjustments for non-routine occupations in England, while no such adjustment occurs for routine occupations. This result is robust to several empirical specifications and varying levels of aggregation. Moreover, firms facing routine occupation shortage are more likely to outsource these vacancies, instead of raising wages or increasing recruitment intensity. In all, these results are consistent with the phenomenon of job polarization and the secular decline of the routine sector. To explore the likely mechanisms at play, we construct a stylized model of search and matching, where labor market islands are characterized by location and occupation types. We demonstrate how, when faced with local labor market shocks, wages in the skill-intensive non-routine sector increase more in response to shortage, thereby raising employment and mitigating the initial shortage, at the expense of the routine sector.

JEL classification: J21, J23, J61, J62.

Keywords: Job Polarization, Migration, Labor Demand, Skill Demand, Skill Mismatch.

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1. Introduction

In 2016, the Conference Board, the US-based organization for business leaders, declared labor shortage to be the key challenge for CEOs in the near future. The lack of workers to fill necessary jobs has stirred much anxiety among policy makers in recent times. Indeed, outside the neoclassical world, labor demand and supply do not clear instantaneously. This is due to frictions in the labor market that cause a discrepancy between the optimal level of employment and the actual one so as to generate distortions in the allocation of labor and in wage setting. In fact, in the most developed economies, anecdotal evidence suggests that a growing number of firms report find it harder to fill their posted vacancies for certain jobs, a phenomenon we call *occupational shortage*. Yet, it has been neither clear nor well explored in the literature if the perceived persistent inability to fill vacancies is just an unsubstantiated complaint or if it actually leads to effective adjustments in wages and employment that eventually clear the market. For these reasons, this paper aims to shed light on the nature of occupational shortage and is the first, to our knowledge, that shows how the interaction of the former with labor market outcomes. To what extent do wages, hours worked and employment respond to changes in occupational shortage? What accounts for differential responses across occupational groups?

In order to address these questions, we begin by examining the empirical evidence. First, we use English micro-data from the UK Employer Skill Survey (ESS) and construct, for each local labor market, occupation group and industry, a measure of shortage, note the reported consequences of shortage and the adopted strategies to counteract it. In particular, we consider 9 geographical markets in England - the North-East, North-West, Yorkshire and the Humber, West Midlands, East Midlands, East of England, London, South-East and South-West, 4 broad occupation groups - Non-Routine Cognitive (e.g. Managers, professionals and related jobs), Routine Cognitive (e.g. Sales and office jobs), Routine Manual (e.g. Production and blue-collar jobs) and Non-Routine Manual (e.g. Service and pink-collar jobs), as well as 14 industry categories. Second, we merge this information with data from the Labor Force Survey (LFS) to study the extent to which labor markets, upon experiencing a higher shortage, adjust. This exercise is carried out on varying levels of aggregation and under different empirical specifications. Third, we investigate whether different types of workers are able to move into pockets of higher shortage and benefit from higher wages. These questions are crucial for a broad understanding of the dynamics of the labor demand and supply, the growing importance of skills, the increase of inequality in both wage and mobility.

From our analysis, we find that occupational shortage varies across time, markets and jobs heterogeneously. In addition, different responses to shortage exist between occupation groups. Indeed, we find that wages, employment and hours worked increases in response to an increase in shortage only for Non-Routine Cognitive (NRC) and Non-Routine Manual (NRM) jobs, while no such response is observed for both Routine Manual (RM) and Routine Cognitive (RC) jobs. This result is robust to different levels of aggregation and empirical specifications. Possible phenomena that could explain these findings include the systemic misreporting of shortage by firms for routine jobs, different levels of matching efficiency across occupation types and the phenomenon of job polarization, well-documented by the likes of Acemoglu and Autor (2011a), which is linked to the secular decline in routine jobs. Our evidence rules out the first two explanations and suggests that the phenomenon of job polarization, driven by routinization, may be at play.

In addition, we find that differential mobility patterns across worker groups. In particular, NRC workers are most likely to move to pockets of the labor market with higher shortage and wages, compared to the other worker groups. It seems, therefore, that workers in other occupation groups are somehow less willing or able to migrate into higher shortage pockets. While preliminary, these results together have profound implications for between-occupation inequality, the future composition of jobs as well as job mobility.

In order to rationalize our empirical findings, we then construct a simple model of search and matching. We consider separate local labor market (islands) where there are only two types of occupation, routine and non-routine. Within each island, firms choose the segment of the market in which to post vacancies while heterogeneous workers decide the type of job to search for. In addition, upon deciding on the type of job for which to search, workers also decide whether or not to migrate to a different island. This is a simple extension of the standard dynamic directed search model as discussed in Guerrieri, Benoit, Kircher, and Wright (2017) and Rogerson, Shimer, and Wright (2005). In equilibrium, there is a threshold above which workers search in the non-routine sector, as well as a threshold beyond which they decide to migrate. Upon calibrating our model, we demonstrate how local labor market shocks that are on average relatively favorable to the non-routine sector can lead to shortage in both the non-routine and routine islands. Yet, while wages and employment increase in response to shortage in non-routine islands, leading to a rapid clearing of shortage in the non-routine islands, this response is muted in routine markets, thereby causing shortage to persist for far longer than in their non-routine counterparts. Furthermore, the existence of mobility costs that are decreasing with respect to skill exacerbates the discrepancy between the non-routine and routine markets. Specifically, higher-skilled workers, who populate non-routine occupations, are more able to migrate across islands in response to local market shocks, relative to less-skilled workers.

The above result therefore serves as a validation of the hypothesis of Skill-Biased Technical change. Indeed, it is through the lens of SBTC that we are able to provide a coherent account of why wage and employment adjustments are observed in response to shortage in non-routine occupations, but not in routine occupations. As such, we can therefore conclude that Skill-Biased Technical change (SBTC) not only accounts for wage and employment growth in non-routine occupations, as documented in the existing literature, but is also the main contributor to the uneven adjustment of labor markets to shortage.

In short, the contribution of this paper is two-fold: (i) it shows that only non-routine markets are able to adjust to shortage, and that (ii) SBTC can account not only for the polarization of the labor market, as documented in the previous literature, bu also can explain the inability of routine markets in mitigating shortage.

This paper is structured as follows: Section 2 briefly reviews the literature on labor market shortage and mismatch. Section 3 introduces the data, the definition of shortage and provides some descriptive results. In Section 4 describes our empirical strategies to study the effect of shortages on wages, hours worked, employment as well as mobility patterns. Section 5 presents the setup of the model and characterizes the equilibrium, while Section 6 examines its calibration. Further discussion of the model's results is provided in Section 7. The last Section concludes.

2. Related Literature

The fundamental law of demand and supply states that prices should adjust to clear the market. As such, the question of shortage should not pose a problem, since wages should rise to eliminate the excess in labor demand so as to clear the market. Nevertheless, the existing literature has tried to reconcile reported evidence of shortage and the classical labor market tenets.

For instance, confronting the claims of a shortage of engineers in the 1950s, Arrow and Capron (1959) argue that engineers' wages simply take time to adjust to clear the market, since firms have to figure out the new equilibrium wage at which they can profitably hire workers. In this sense, shortage can be a transitory phenomenon. Nonetheless, the authors show that if demand were to increase continually and prices are slow to respond, a situation of chronic shortage could occur and would only be alleviated with a halt in the demand increase. In a similar vein, Freeman (1975) considers the responsiveness of the supply of physics graduates to salaries in the period from 1943 to 1975, when the demand for physicists varied substantially, and finds that the number of labour market entrants with physics degrees varied closely with salary incentives, albeit with a lag. Hence, the supply of graduates eventually responded to changes in the salaries caused by shifts in demand, even if this adjustment took some time. More recently, the issue of shortage arising from a lack of requisite skills has also been addressed by Cappelli (2005). Addressing reports of skills shortage among employers in the United States, he finds little concrete evidence to support their claims. Instead, he argues that the decline of in-house training as well as current recruitment practices are behind these reports. Moreover, he shows that in certain occupations where reports of shortage have been most rife, wages and posted vacancies have actually declined, contrary to the basic laws of demand and supply. Similarly, Rathelot et al. (2017) suggests that shortage appears to be demand-side problem, as employers' wage setting policies appear not to reflect existing shortages.

How shortage should be measured is a matter of contention. The aforementioned papers have largely relied on anecdotal reports of shortage, partly due to a lack of empirical measures.

Since the Job Openings and Labor Turnover Survey (JOLTS) data has been made available, some authors have begun examining the ability of firms to fill their vacancies, which could be considered a proxy for shortage. In their paper, Davis, Faberman, and Haltiwanger (2013) examine the rate at which firms fill vacancies using the JOLTS data at the establishment level. They find that the vacancy-filling rate varies greatly between industries, falls with increasing employment and rises with firm growth. They also find that firms not only influence their vacancy-filling rates via their vacancy posting decisions, but also by altering their recruitment intensity, which they then seek to measure using a recruitment intensity index.

However, as an indictment to ability of the JOLTS survey in documenting vacancies, the authors find that 41.6 percent of hires actually occur at firms who do not report any vacancies. Moreover, as vacancy duration is not provided in JOLTS, the distinction between vacancies and persistently unfilled vacancies (i.e. shortage) is unclear. By adopting a more explicit measure of shortage, this paper endeavours to do better in this respect using the UK dataset.

Apart from the above papers which discuss the incidence of shortage, the existing literature has also sought to explain shortage, and the lack of corresponding wage and employment adjustments. In fact, a line of literature on wage curves, beginning with Blanchflower and Oswald (2005), presents evidence that areas with high unemployment are characterized by lower wages, directly contradicting the classical model. Using microeconomic data on several countries, including the US and countries in continental Europe, Blanchflower and Oswald (2005) and Card, Blanchflower, and Oswald (1995) estimate the elasticity of pay to unemployment to be -0.1, meaning that a one percentage point increase in unemployment lowers wage by 0.1 percent, a finding that is robust across different countries. They rationalize this result by adopting the model of efficiency wages. In such a setup, employers pay employees a sufficiently high wage to discourage shirking. Since higher unemployment lowers the outside option of the worker, employers are able to lower the wage, while still encouraging effort. This framework could thus explain why shortages do not seem to dissipate even with higher observed wages.

Labor market mismatch can also be considered as a potential cause of shortage. It is defined as the coexistence of vacancies and the unemployed located in different labor markets. In this respect, mismatch leads to a higher unemployment rate than what would occur if the unemployed met and matched with unfilled vacancies. This stems from the idea that, despite the high numbers of jobseekers, firms are unable to fill their vacancies as the unemployed are searching in the 'wrong' markets, which can be characterized, for instance, by geographical location, occupations or industries. Shortages in a given labor market can dissipate so long as there is inter-market mobility. Looking at relative wages between different geographic locations in the US, Topel (1986) studies how internal migration arbitrages these wage differences to an extent. Using CPS data, Topel (1986) finds that wages are sensitive to inter-regional labor market differences, via the channel of migration, which is in turn limited by mobility costs. Using a dynamic model where workers' expectations of local demand and wages determine their decision to migrate (or not), he shows that there is continuous adjustment towards the equilibrium, as workers get updates on the current and expected future state of each local economy. Likewise, Enrico (2011) considers why persistent divergence in wages and productivity occurs between different local labour markets in the US and explains this using a static version of Topel (1986) with imperfect elasticity of labour and housing supply.

Apart from geographical labor market mismatch, the literature has also considered sectoral and occupational mismatch. This includes Herz and Van Rens (2015), who define mismatch unemployment as the unemployment arising from dispersion in labor market conditions across labor market segments, differentiated by geography or industry. They measure the roles of four types of frictions that generate mismatch: worker and firm mobility costs, wage rigidities and matching efficiency heterogeneity. They argue that both geographical and industry mismatch are due to wage rigidity while industry mismatch is also partly accounted for by limited firm mobility. They also show that states with high wages also have low profits, implying that states that are attractive to firms are also unattractive to workers and vice versa, resulting in inter-state mismatch unemployment and unfilled vacancies.

Shortage can also exist in a world without labor market rigidities. For instance, Shimer (2007) shows how mismatch can exist even if wages are set competitively. Characterizing a local labor market by occupation and geographical location and allowing for the random allocation of jobs and workers to labour markets, he shows that at any instant, even if wages are competitive in every market, there will be some markets with labour shortages and others with unemployment, which would otherwise not exist in a unified labour market.

Nonetheless, the empirical evidence suggests that mismatch may not be an especially severe phenomenon. For example, Sahin, Song, Topa, and Violante (2014) estimate that mismatch unemployment accounts for at most one third of the increase in the unemployment rate following the Great Recession in the US, by comparing the empirical unemployment rate to the unemployment rate that would arise if a social planner were able to reallocate workers between occupations and sectors such that the productivity-weighted market tightness across labor markets were equalized. In addition, they find that mismatch unemployment accounts for a bigger fraction of the unemployment rate among the highly-educated than the less-educated. Similarly, Daly, Hobijn, Sahin, and Valletta (2012) show that while the natural unemployment rate in the US increased by one percentage point compared to before the Great recession, this rise cannot be attributed to an increase in mismatch unemployment. In fact, they find that the increase in mismatch unemployment has been limited, and the rise in the unemployment rate can be attributed instead to the extension of unemployment insurance benefits during the recession. Moreover, there is some evidence from the US to suggest that occupational and industry mobility is fairly high, which begs the question as to whether mismatch unemployment is a persistent problem. For example, using PSID data from 1968 to 1997, Kambourov and Manovskii (2008) find that occupational and industrial mobility in the US is high and increasing over this period and cuts across all education levels. Also, occupational mobility is found to be slightly pro-cyclical. Even so, one wonders if this conjecture still holds in the present day and for other countries.

Related to this paper as well is the literature on skill-biased technical change and routinization. Starting from Autor, Katz, and Krueger (1998), many authors have examined how SBTC has increased wage inequality between skill groups since the 1970s. More recently, authors have pointed to how SBTC, along with routinization, can account for wage and job polarization in several industrialized economies. The routinzation hypothesis is closely linked to SBTC, and relates to the advent of machines that have replaced workers in routine jobs.

For instance, Acemoglu and Autor (2011b) show that over the past three decades in the United States, due to opportunities for off-shoring and mechanization that substitutes for the labor of routine (middle-skill) workers, employment in abstract (high-skill) and service jobs have increased relative to that of routine (middle-skill jobs), a phenomenon they term 'job polarization'. They also document 'wage polarization', a related phenomenon where the wages of high and low earners in the wage distribution have risen in the past three decades relative to that the median earner. The decline of routine jobs in the US labor market has also been documented and discussed in Autor, Levy, and Murnane (2003), Autor and Dorn (2013), Autor, Katz, and Kearney (2006b), Autor and Handel (2013), as well as Autor, Katz, and Kearney (2006a).

Job polarization has also been documented in the United Kingdom. Goos and Manning (2007) and Goos, Manning, and Salomons (2014) document the increase in employment shares in top and bottom paid jobs, along with a decline in the wages of middling earners relative to those of top and bottom earners, in line with the routinization seen in the United States. While the literature has hitherto not made a link between routinization, polarization and occupational shortage, the results found in this paper suggest that the differential responses of routine and non-routine jobs may plausibly attributed to the decline of the routine sector.

This paper bridges the two hitherto disparate strands of literature regarding shortage and skill-biased technical change. Indeed, apart from constructing a concrete measure of shortage, we are also able to demonstrate how SBTC, along with routinzation, can account for the differences between routine and non-routine sectors in their abilities to mitigate shortage.

3. Data and Descriptive Statistics

Having discussed the literature, we now proceed to describe the data.

3.1. *Data on firms and workers*

We use the UK Employer Skill Survey (ESS) and the UK Labor Force Survey (LFS) to conduct our empirical analysis. The ESS is a firm-level survey published by the UK Commission for Employment and Skills (UKCES). It was first carried out in 1999 only for England for a sample 26,952 firms.This sample was drawn from England's business database, which comprises of all business establishments in the UK with more than five employees and sample weights are provided. It was then conducted again in 2001 and 2002 for a cross section of firms in England. There was a hiatus until the survey was re-conducted in 2011 and 2013, by which time it had expanded to include the whole of the UK, garnering a sample of 91,279 firms (75,255 for England alone). The survey was also conducted recently in 2015, although the dataset has not yet been made available for that year.

Apart from basic information on the industry to which the firm belongs, the number of employees, the regional location of the firm and its headquarters and whether it is from the public or private sector, several questions are asked of firm respondents regarding their ability to meet their employment needs. These include the number of posted vacancies they have at the time of the survey, the breakdown of posted vacancies according to each occupation type, the number of vacancies they find hard-to-fill, the breakdown of hard-to-fill vacancies according to each occupation type, why they find these vacancies hard-to-fill, the strategies that they would adopt to try to fill those vacancies as well as the consequences they have already faced from their inability to fill those vacancies.

The LFS is a quarterly survey of individuals' labor market experiences that has been conducted since 1992. It contains key information such as income, hours worked, employment status and history, industry, region as well as on basic individual characteristics such as age and gender. Approximately 100,000 people are interviewed at each quarterly wave, and each individual is surveyed for five such waves until he/she drops out of the sample and is replaced. Since the ESS does not have any data on wages and hours worked for each occupation in the firm, it can be supplemented with the data from the LFS. In addition, the LFS provides information on workers' occupational and geographic mobility, which will be important for our analysis later on.

3.2. *The definition of shortage*

As previously mentioned, there is no reliable measure of shortage in other commonly-used firm-level datasets. The JOLTS, for instance, does not have any information on how long vacancies have been left unfilled. As such, for gauging shortage, these datasets can only provide a ratio of hires to vacancies, which is problematic since there is no objective threshold beyond which a shortage can be declared. On the contrary, the ESS asks firms directly about the number of vacancies that they find difficult to fill[1]. While vacancy duration was not consistently asked in the ESS as well, this direct assessment by firms is arguably a much more reliable measure of shortage than what is given in most datasets such as JOLTS. In addition, since this question is asked for every occupation the firm has, we are able to construct a measure of shortage for each occupation type.

3.3. Incidence of shortage and variations over time

Table 1 presents some summary statistics on the number of vacancies and hard-to-fill vacancies reported by firms in all waves of the survey. It also reports the share of hard-to-fill vacancies, given by $\frac{\text{No. of hard-to-fill vacancies}}{\text{Total number of vacancies}}$. From the table, the incidence of shortage appears to be declining in from 1999 to 2013. Yet, shortage remains a substantial, with the fraction of shortage averaging around 0.3 in 2013.

Heterogeneity in the incidence of shortage between occupations can also be observed over time. Figures 1 and 2 show the short-term change in the share of hard-to-fill vacancies between the survey waves from 1999 to 2001, and 2011 to 2013 respectively. As can be seen from Figure 1, shortage incidence increases for NRC jobs from 1999 to 2001, while declining for other job types over this period. From 2011 to 2013, as seen in Figure 2, shortage share increases for all occupations and rises the most for NRM and NRC jobs. Cross-refering to Table 1, this rise in shortage share is not so much due to a decline in reported vacancy posting, but instead stems from an increase in the number of hard-to-fill vacancies.

From these descriptive results on the incidence and evolution of shortage over time, it is apparent that there is some variation of shortage over time and across occupations. Appendix A also documents the changes in shortage across industries and regions. This variation in shortage at the region, industry and occupation level is exploited later on in our empirical analysis.

3.4. On firms' strategies in dealing with shortage

In the ESS, firms were also asked how they intended to deal with their shortage problems. Firm respondents were allowed to choose from an array of options. As shown in

[1]Specifically, the question asked is the following: How many vacancies for (occupation code) are proving hard-to-fill?

Table 1: Shortage share over survey waves

	NRC			RC		
	# HTF	# vacancies	Share	# HTF	# vacancies	Share
1999	57403	134411	0.427	96345	241754	0.398
2001	117183	232219	0.504	120303	281733	0.427
2002	78575	177923	0.441	83601	216504	0.386
2011	38669	172816	0.223	37407	158703	0.235
2013	60123	189796	0.316	41301	164678	0.250

	RM			NRM		
	# HTF	#vacancies	Share	# HTF	# vacancies	Share
1999	33358	60169	0.554	59833	121322	0.493
2001	33756	69367	0.486	84522	179505	0.470
2002	22519	52183	0.431	57812	114901	0.503
2011	4786	28520	0.167	25288	129694	0.194
2013	8524	24348	0.350	45701	152589	0.299

Fig. 1. Change in shortage share between 1999 and 2001 by occupation type

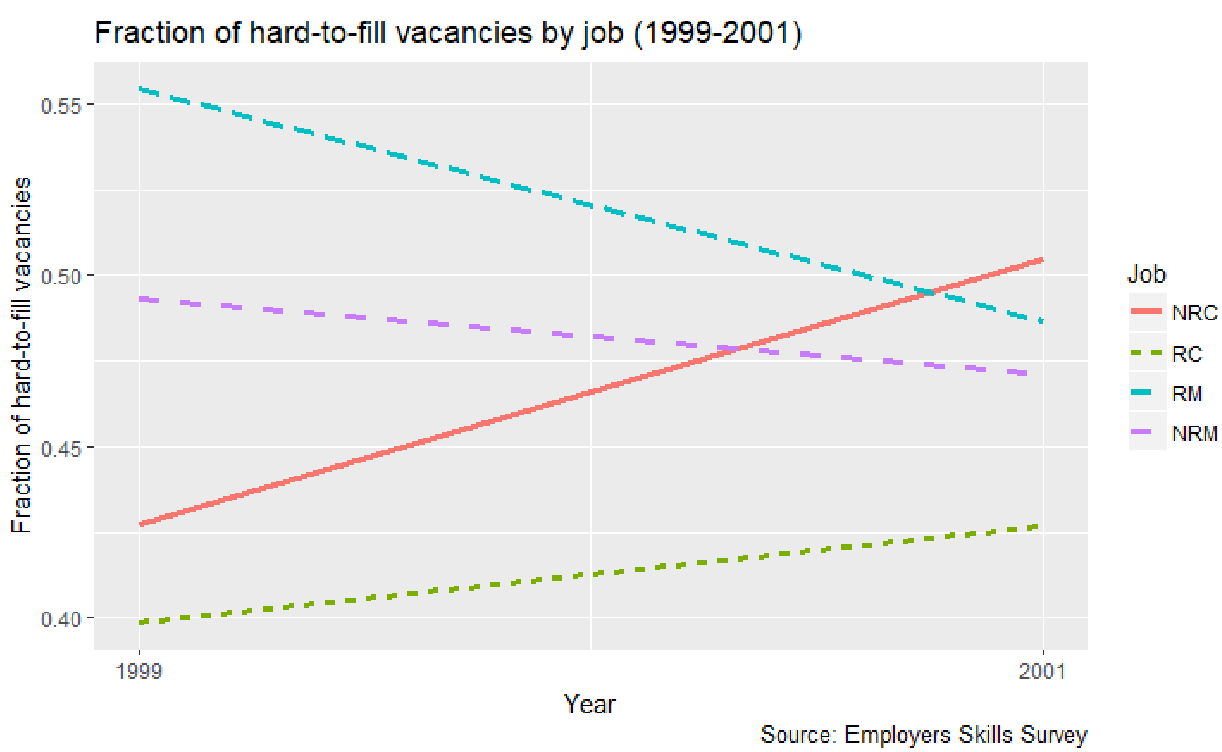


Fig. 2. Change in shortage share between 2011 and 2013 by occupation type

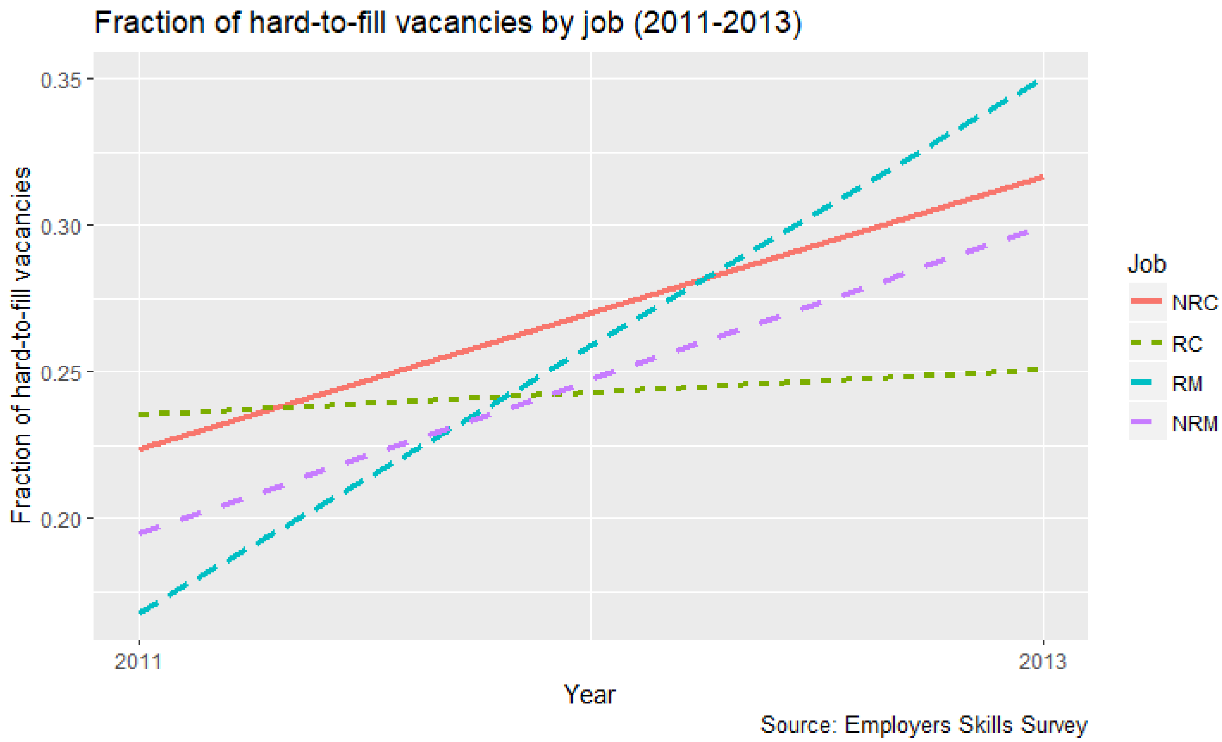


Table 2: Strategies reportedly used to tackle shortage

	Mostly NRC	Mostly RC	Mostly RM	Mostly NRM
Increase salary	0.059	0.042	0.033	0.042
Provide training for incumbents	0.085	0.080	0.050	0.092
Redefine existing jobs	0.134	0.123	0.122	0.118
Increase recruitment intensity	0.378	0.382	0.364	0.464
Increase trainee programmes	0.089	0.072	0.055	0.068
Use new recruitment methods	0.372	0.306	0.321	0.330
Hire foreigners	0.043	0.027	0.029	0.048
Hire contractors	0.096	0.051	0.052	0.048
Train less qualified recruits	0.073	0.066	0.045	0.059
Increase job attractivity	0.017	0.011	0.014	0.010
Other	0.042	0.046	0.045	0.027
Nothing	0.127	0.132	0.149	0.107
Don't know	0.014	0.022	0.027	0.028
No. of obs	1766	1815	2736	2835

The table shows the percentage of firms that adopt the above strategies to tackle occupational shortage. Firms are allowed to cite more than one strategy, so the percentages do not sum to 1.

Table 2, which uses data from the 2011 and 2013 waves, firms were most likely to increase search intensity in attempting to fill hard-to-fill vacancies. The next two most commonly cited strategies were 'redefine existing jobs', where existing employees perform the tasks of unfilled vacancies, and 'nothing'. Notably, raising wages and raising job attractiveness were the least cited strategies firms would adopt. Some differences exist between the 4 broad occupation groups. For instance, firms with predominantly routine shortage more frequently cite doing "Nothing", while firms with predominantly NRC shortage more frequently cite "Raising wages".

To illustrate whether any of these differences in reported strategies are statistically significant, Figures 3 and 4 present estimated marginal effects of simple probit regressions of the select strategy choices on firm type category and controls such as industry, firm size and region. Specifically, we consider whether or not key strategies, including raising wages and increasing recruitment intensity, vary significantly across firms facing different shortage types. We then run a probit regression with a set of firm controls including firm size, region and industry fixed effects, where the dependent variable is a dummy equaling one if the firm reports adopting that strategy in response to shortage and zero otherwise. The marginal effects of having predominantly NRC, RC, RM, NRM on the strategies chosen are then plotted in Figures 3 and 4.

As seen from Figures 3 and 4, firms facing shortage in NRC occupations are significantly more likely to claim to increase recruitment intensity than those facing shortage in RC and RM occupations, while firms with most of their shortage in NRM occupations are significantly more likely to increase recruitment intensity than those with shortage in RM occupations. As for wages, we find that firms with most of their shortage in NRC occupations more likely to claim to increase wages than all other firm types.

Having gone through firms' reported strategies to deal with shortage, it should be noted that there is no way to verify that firms even carried out these strategies and hence whether their claims had any impact on labor market outcomes. As such, we consider outcomes such as wages, hours worked and employment from the LFS to verify these ostensibly adopted measures.

Fig. 3. How predominant shortage type affects probability that the firm increase recruitment intensity

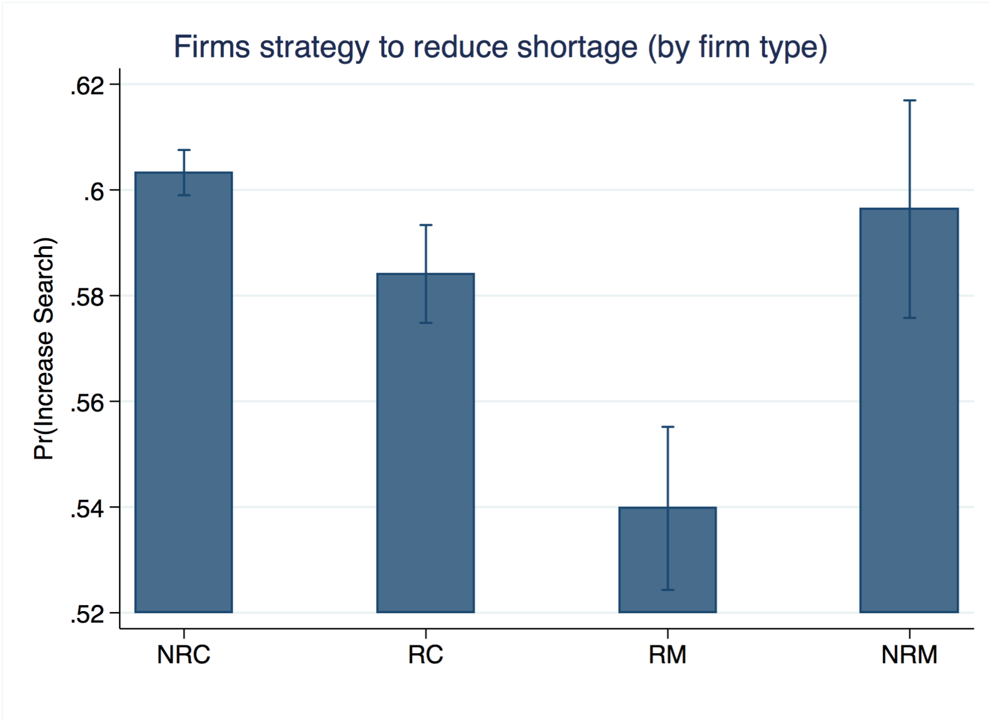
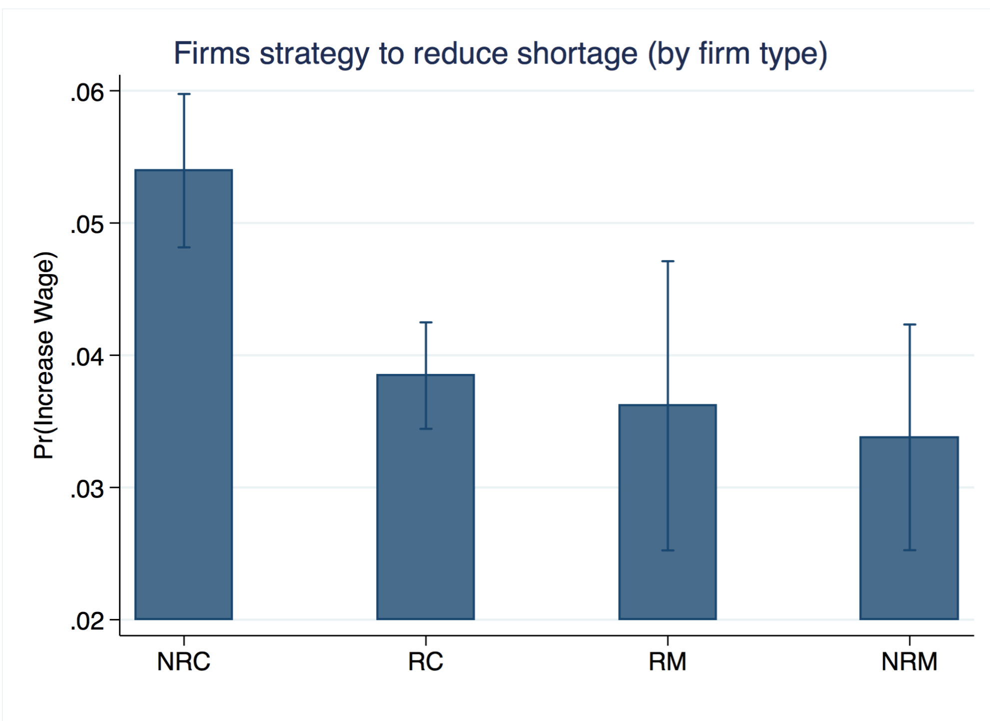


Fig. 4. How predominant shortage type affects probability that the firm raises wages



4. Empirical strategies

Here, we estimate the effects of shortage on key labor market outcomes - hourly wages, hours worked and employment. Using several empirical strategies, we obtain a consistent takeaway, that shortage leads to significant change in labor market outcome changes for non-routine occupations but does not affect outcomes for routine occupations.

4.1. Individual Level Regression with Bartik Instruments

As the first empirical exercise, we run an individual-level regression model inspired by Acemoglu, Autor, and Lyle (2004). We consider how labor market outcomes change when shortage changes between two periods. The labor market outcomes we examine are hourly wages, hours worked and employment. In our analysis, we consider a change in shortage between 1999 and 2001, as well as between 2011 and 2013. These years were chosen for analysis due to ESS data availability. This regression is run *separately* for each of the four occupational categories.

$$y_{i,r,s,t} = \alpha_0 + \alpha_1 T + \alpha_1 T * \Delta Shortage_{r,s,t} + \beta_2 X_{i,r,s,t} + \gamma_r + \gamma_s + \gamma_t + \epsilon_{i,r,s,t}$$

Where $y_{i,r,s,t}$ is the job market outcome (logged) for individual i at region r, industry s and time t, $X_{i,r,s,t}$ are the controls for individual i in region r, industry s at time t. γ_r, γ_s and γ_t are region, industry and year effects. $\epsilon_{i,r,s,t}$ is the error term. $\Delta Shortage_{r,s,t}$ is the change in shortage share (logged) in region r and industry s in the two years up to year t, where shortage share in a given occupation type is defined as $\frac{\text{No. of hard-to-fill vacancies in } r,\ s,\ t}{\text{Total no. of vacancies in } r,\ s,\ t}$. Let T be a dummy equaling 1 if the year is 2001 or 2013 and 0 if the year is 1999 or 2011. It is helpful to think of the change in shortage as a 'treatment' that an individual in a given occupation type undergoes while belonging to that region r, industry s at time t.

One concern is that $\Delta Shortage_{r,s,t}$ is likely endogenous, since other unobserved factors time-varying local labor market conditions that affect wages, hours worked or employment are probably affecting shortage as well. As such, we use Bartik instruments as IVs for the shortage variable. Consider, for example, employment. Then, for each occupational category, the Bartik instrument is the following:

$$\widehat{Employment}_{r,s,t} = \Big[\frac{Employment_{NATION,s,t}}{Employment_{NATION,s,t-2}}\Big] * Employment_{r,s,t-2}$$

$$Shock_{r,s,t} = \widehat{Employment}_{r,s,t} - Employment_{r,s,t-2}$$

where $\widehat{Employment}_{r,s,t}$ is the expected employment in region r, industry s at time t for a given occupation type if employment had grown at the national rate for industry s over the past two years. The Bartik instrument is thus the growth in employment in region r, industry s that would have occurred between t and $t-2$ had it grown at the national rate for industry s.[2] This 'demand shock' is orthogonal to any changes in local labor market conditions at time t. Yet, this demand shock is also correlated with shortage, rendering it a valid IV.[3]

Tables 3 and 4 show the regression results, for each of the four occupation categories, in the individual-level regressions where the outcome variables are log hourly wage and log hours worked. Thus, α_1 can be interpreted as the percentage change in an individual's labor market outcome due to a one percentage increase in $\Delta Shortage_{r,s,t}$. Standard demographic controls including age, education, gender, ethnicity, as well as fixed effects for region, industry and survey wave are added. As seen in Table 3, a higher shortage increases wages significantly for NRC and NRM jobs, but leads to no significant change for RC and RM jobs. On the other hand, while a rise in shortage increases the number of hours worked significantly for employees in NRC only, it does not not for RC, RM and NRM jobs.

Table 5 shows the regression results for the four categories with employment as the outcome variable. How does a change in shortage affect the probability that an individual is employed in a region and industry? For each of the 4 occupation categories, we let $y_{r,s,t} = 1$ if an individual is employed in industry s and region r at time t and 0 otherwise. A probit regression with the Bartik instruments is given Table 5. From Table 5, an increase in shortage in NRC and NRM occupations significantly increases the probability that individuals are employed in NRC and NRM jobs respectively. In contrast, a rise in shortage in RC and RM jobs lead to a significant *decrease* in the probability of being employed in those occupations.

The individual-level regressions thus show that the while wages, hours worked and probability of employment increase significantly when the change in shortage increases for NRC and NRM occupations, this is not true for RC and RM occupations. Does the same distinction between routine and non-routine occupations hold on the aggregate level using different empirical strategies? We study this in the next section.

[2]Following Goldsmith-Pinkham, Sorkin, and Swift (2018), when we compute the national employment growth rate for a specific industry and occupation, we exclude the region-industry cell for which we are building the instrument.

[3]See Appendix B for the first stage regressions and the validity of the Bartik instrument.

Table 3: Shortage and Wages (2SLS)

	(1) w^{NRC}	(2) w^{RC}	(3) w^{RM}	(4) w^{NRM}
$\Delta Shortage_{r,s,T=1} * T$	0.624**	-0.289	-0.396	0.0967***
	[0.250]	[0.385]	[0.289]	[0.026]
$FE\ (reg, ind, wave)$	Yes	Yes	Yes	Yes
$Controls$	Yes	Yes	Yes	Yes
N	13031	10673	2931	9275
R^2	0.301	0.343	0.188	0.224

t statistics in brackets; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Shortage and Hours (2SLS)

	(1) hrs^{NRC}	(2) hrs^{RC}	(3) hrs^{RM}	(4) hrs^{NRM}
$\Delta Shortage_{r,s,T=1} * T$	0.119*	0.141	-0.143	-0.118
	[0.072]	[0.276]	[0.162]	[0.169]
$FE\ (reg, ind, wave)$	Yes	Yes	Yes	Yes
$Controls$	Yes	Yes	Yes	Yes
N	17674	1784	1132	2606
R^2	0.021	0.107	0.088	0.095

t statistics in brackets; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Shortage and Employment Pr. (2SLS)

	(1) e^{NRC}	(2) e^{RC}	(3) e^{RM}	(4) e^{NRM}
$\Delta Shortage_{r,s,T=1} * T$	3.625**	-4.725**	-0.226	1.532*
	[1.837]	[2.356]	[0.164]	[0.861]
$FE\ (reg, ind, wave)$	Yes	Yes	Yes	Yes
$Controls$	Yes	Yes	Yes	Yes
N	74018	74018	74018	74018
R^2	0.071	0.003	0.174	0.021

t statistics in brackets; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2. Aggregate Level Regression - Dynamic GMM

For each occupation category, we run a dynamic Generalized Method of Moments (GMM) model to ascertain if our previous results hold when using region-industry level data instead. Individual-level data on wages and hours worked are aggregated such that for each region, industry and occupation type, an average of wages and hours worked is constructed. In addition, the average employment rate for each region, industry and occupation type is measured in the following way. First, individuals living in a given region are considered affiliated to a given industry and occupation type if they are currently employed in this industry and occupation *or* if they are currently unemployed but their previous job belonged to this industry and occupation type. Then, the region r, industry s and occupation j level employment rate at time t is defined as $\frac{\text{No. employed}_{j,r,s,t}}{\text{No. employed}_{j,r,s,t}+\text{No. unemployed}_{j,r,s,t}}$. For each occupation type j, a separate regression is run. The regression model is as follows

$$y_{r,s,t} = \alpha + \beta_0 y_{r,s,t-1} + \beta_1 Shortage_{r,s,t} + \beta_2 X_{r,s,t} + \gamma_r + \gamma_s + \epsilon_{r,s,t}$$

Where $Shortage_{r,s,t}$ is $\frac{\text{No. of hard-to-fill vacancies}_{r,s,t}}{\text{Total no. of vacancies}_{r,s,t}}$. $y_{r,s,t}$ is the job market outcome in region r, industry s, and year t, $X_{r,s,t}$ consists of control variables that affect outcomes $y_{r,s,t}$ for in region r, industry s, and year t, γ_r and γ_s are regional and industry fixed effects respectively.

Taking the first difference to eliminate the fixed effects, we obtain for each occupation type j

$$\Delta y_{r,s,t} = \beta_0 \Delta y_{r,s,t-1} + \beta_1 \Delta Shortage_{r,s,t} + \beta_2 \Delta X_{r,s,t} + \Delta\epsilon_{r,s,t}$$

$\Delta y_{r,s,t-1}$ is clearly endogenous. Moreover, it is not unreasonable to think that $\Delta Shortage_{r,s,t}$ and $\Delta X_{r,s,t}$ would be correlated with $\Delta\epsilon_{r,s,t}$. As such, we adopt the Arellano-Bond estimator by using the lags of the regressors as instruments. Note that while wage, hours worked and employment data provided by the LFS is available for every year from 1999 to 2013, the same cannot be said of the data on shortage, since the ESS was only conducted in five waves over that period of time. As such, we impute data for the years during which the ESS was not conducted, and we do it through moment-conserving interpolation.[4] Tables 6, 7 and 8 present the results. As seen from the tables, the results tell a similar story to that told by the individual-level regressions with Bartik Instruments. While for routine jobs, wages, hours worked and employment rates increase significantly in response to an increase in shortage,

[4]For each occupation, we extract correlations of our measure of occupational shortage with LFS variables for the years when the ESS was conducted. Then, we compute moments (correlations) preserving approximations of missing data point through polynomials and splines.

no significant response is observed for non-routine jobs.

Table 6: Shortage and Wages (DGMM)

	(1) w^{NRC}	(2) w^{RC}	(3) w^{RM}	(4) w^{NRM}
L.Hourly wage	0.110	0.084**	0.106***	0.099*
	[0.069]	[0.037]	[0.037]	[0.054]
Shortage	0.032***	0.001	-0.007	0.029**
	[0.012]	[0.009]	[0.014]	[0.011]
Participation rate	-0.007	0.004	- 0.000	0.088*
	[0.039]	[0.050]	[0.031]	[0.046]
$FE\ (reg, ind, year)$	Yes	Yes	Yes	Yes
$Controls$	Yes	Yes	Yes	Yes
N	2139	2139	1947	1992

t statistics in brackets; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
errors clustered at r, s level

4.3. *Aggregate results - VECM*

In this section we study the aggregate effects of shortage on labor market outcomes. In particular, for each occupation category we consider the following VAR/VECM model:

$$\Delta X_t = \sum_{j=1}^{L-1} \beta_j \Delta X_{t-j} + \Pi X_{t-1} + \epsilon_{t+1}$$

Vector X contains logs of the hourly wage, employment rate, hours worked and our measure of shortage. Although all variables exhibit unit root, there is a cointegrating equation when considering variables for NRM jobs. This implies that a simple VAR in difference would be incorrect and deviations from a long-run equilibrium must be kept into account. Such correction, here captured by Π, transforms the VAR in difference into a VECM when considering NRC variables. For each occupation, the optimal number of lags is chosen via LR information criteria (2 lags when considering NRC jobs, 2 for RC, 3 for RM, 2 for RM).

As Figures 5 to 8 show, a one percentage increase in shortage leads to a significant adjustment in wages, and employment and hours worked for NRC and NRM occupations. It is worth to notice the intriguing pattern of hours: as shortage hikes, the immediate adjustment is through the intensive margin; only through time does the extensive margin

Table 7: Shortage and Hours (DGMM)

	(1) hrs^{NRC}	(2) hrs^{RC}	(3) hrs^{RM}	(4) hrs^{NRM}
L.Hours worked	0.169	0.236***	0.046	0.012
	[0.152]	[0.057]	[0.056]	[0.073]
Shortage	0.014***	0.016	-0.013	0.019*
	[0.005]	[0.010]	[0.013]	[0.011]
Hourly wage	-0.036	-0.092	0.181**	0.389***
	[0.040]	[0.126]	[0.077]	[0.102]
$FE\ (reg, ind, year)$	Yes	Yes	Yes	Yes
$Controls$	Yes	Yes	Yes	Yes
N	2139	2139	1947	1992

t statistics in brackets; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
errors clustered at r, s level

Table 8: Shortage and Employment rate (DGMM)

	(1) e^{NRC}	(2) e^{RC}	(3) e^{RM}	(4) e^{NRM}
L.employment rate	0.336***	0.320***	0.305***	0.045
	[0.041]	[0.042]	[0.059]	[0.043]
Shortage	0.008**	0.000	0.003	0.071*
	[0.003]	[0.003]	[0.002]	[0.041]
Participation rate	-0.008	0.030*	0.001	0.963***
	[0.011]	[0.018]	[0.006]	[0.169]
$FE\ (reg, ind, year)$	Yes	Yes	Yes	Yes
$Controls$	Yes	Yes	Yes	Yes
N	2139	2139	1947	1992

t statistics in brackets; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
errors clustered at r, s level

Fig. 5. Impulse Response Function (IRF) for NRC jobs

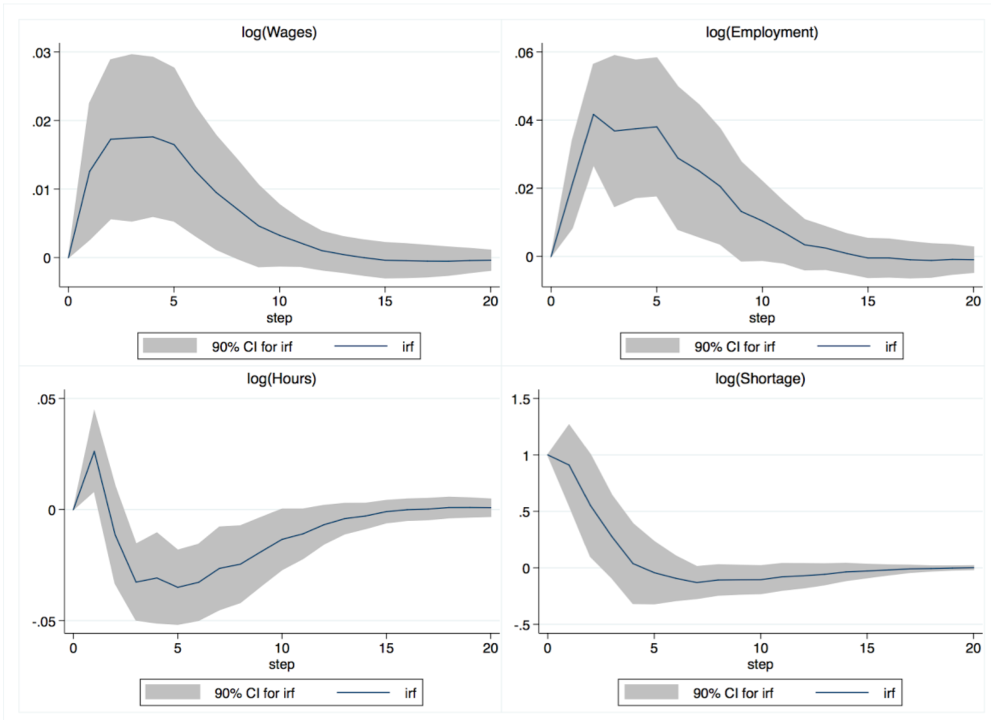


Fig. 6. Impulse Response Function (IRF) for RC jobs

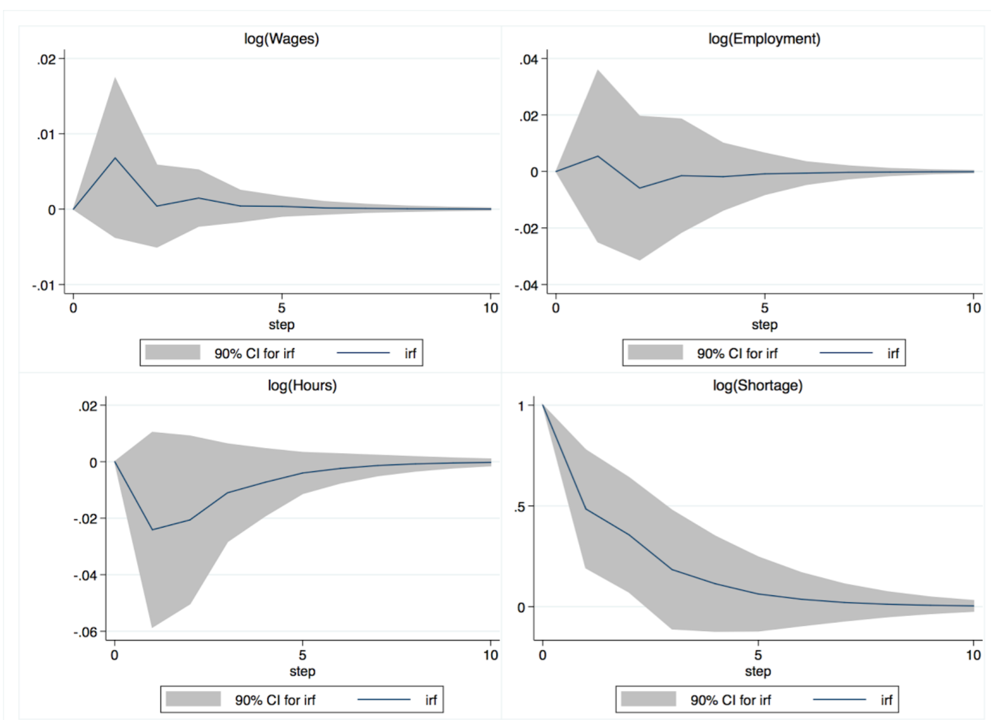


Fig. 7. Impulse Response Function (IRF) for RM jobs

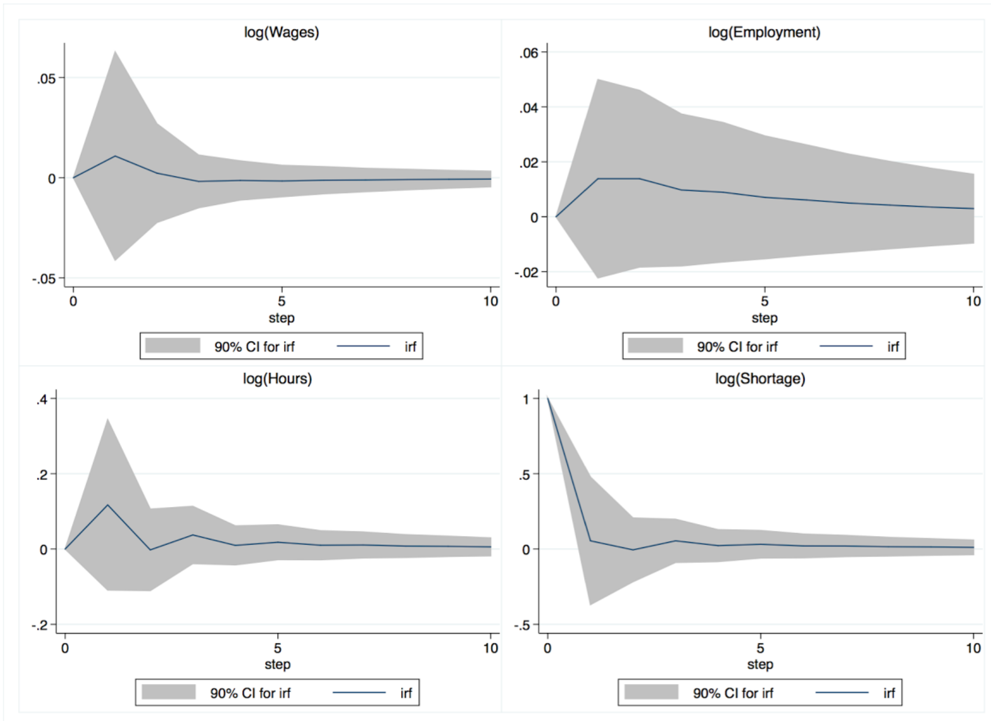
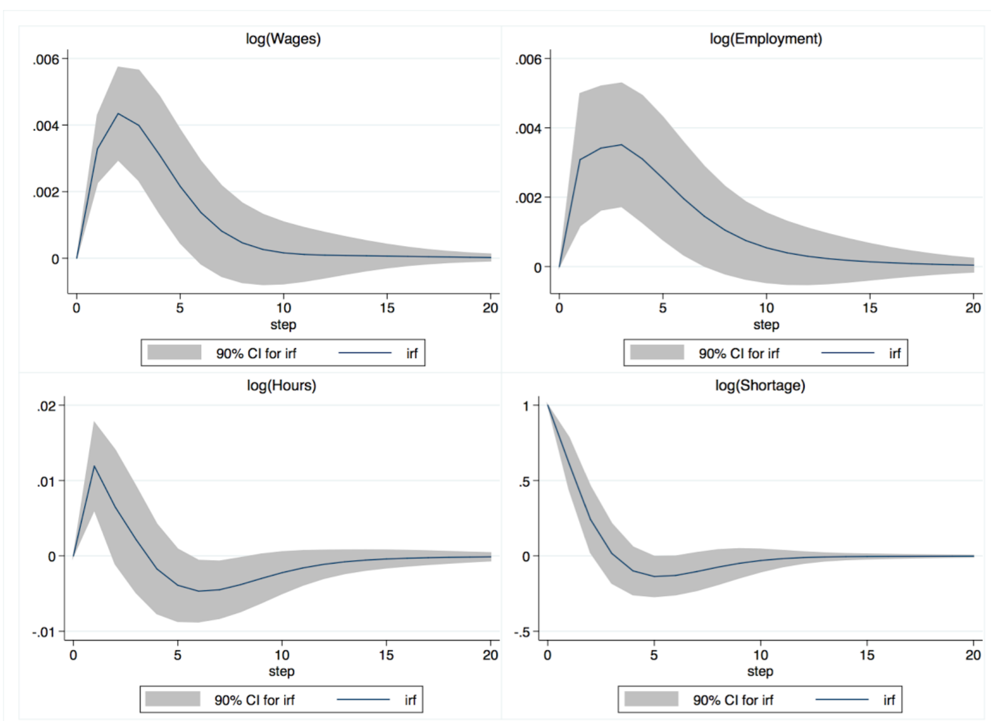


Fig. 8. Impulse Response Function (IRF) for NRM jobs



adjust while wages and hours worked diminish. We observe the same pattern for NRM job, even though the magnitude of the adjustments of employment and wages is almost ten times smaller with respect to NRC jobs. On the other hand, we do not observe a significant effect of shortage on any other variable for RC and RM occupations, suggesting that these markets -typically heavily hit by polarization- find it difficult to adjust (Figures 6 and 7).

4.4. Making sense of the results

While the results consistently show that a rise in wages, hours worked and employment for non-routine occupations only, the question remains as to what drives these differences between routine and non-routine occupations. Before embarking on a theoretical model, we inspect the data further to reject or ascertain some possible hypotheses. We consider the following: that there is systemic misreporting of shortage for routine vacancies, that firms with hard-to-fill routine vacancies eventually outsource or mechanize them instead of raising hours or wages and lastly, that instead of an occupation-based distinction, firms with predominantly routine vacancies may be inherently less adept at filling their vacancies.

4.4.1. Systemic misreporting of shortage for routine vacancies

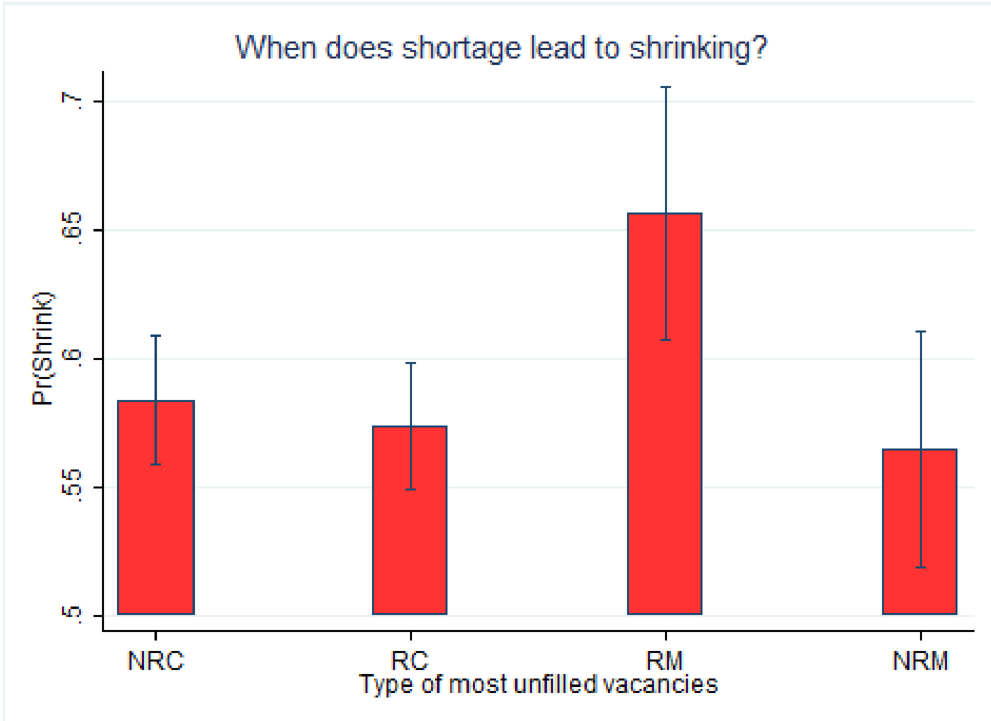
The simplest explanation for the above results could be that routine vacancies are systemically misreported in the ESS, such that hiring managers consistently over-report shortage in routine jobs. Why this should be so is unclear, but we check for other evidence that shortages in routine occupations have substantive impact to refute the notion that they are empty claims. In the ESS, if a firm had at least 1 hard-to-fill vacancy in any occupation, it was asked about the consequences of shortage for the firm. Specifically, firms were asked if they had ended up shrinking their businesses or resorting to outsourcing and mechanization as a consequence of their shortage problem. While these consequences are not independently verifiable, they give us an idea of whether shortages in routine occupations actually matter, even if these are rather descriptive.

We first run the following probit regression.

$$Pr(\text{Shrink})_{i,t} = \alpha + \beta \text{ Firm Type}_{i,t} + \gamma X_{i,t} + \epsilon_{i,t}$$

Where $Shrink_{i,t}$ is a dummy equaling 1 if the firm says that the shortage is causing them to shrink their operations, *Firm type*$_{j,t}$ refers to whether the firm has a majority of NRC, RC, RM or NRM hard-to-fill vacancies and $X_{i,t}$ consists of controls such as the size of the firm, the industry and region in which it operates.

Fig. 9. The effect of shortage type on the probability that the firm shrinks its operations



As shown in Figure 9, regardless of the kind of shortage they predominantly face, all firm types have a significantly positive probability of shrinking as a result of shortage. Also, firms facing shortage mainly in RM occupations are significantly more likely to shrink than firms facing shortage in other occupations, thereby suggesting that claims of shortages in RM occupations have substantive impact and may not be wholly empty.

In a similar vein, we next show that firms with shortages in RC occupations are significantly more likely to outsource. This finding also lends credence to claims of shortage for routine occupations.

4.4.2. Outsourcing and mechanization

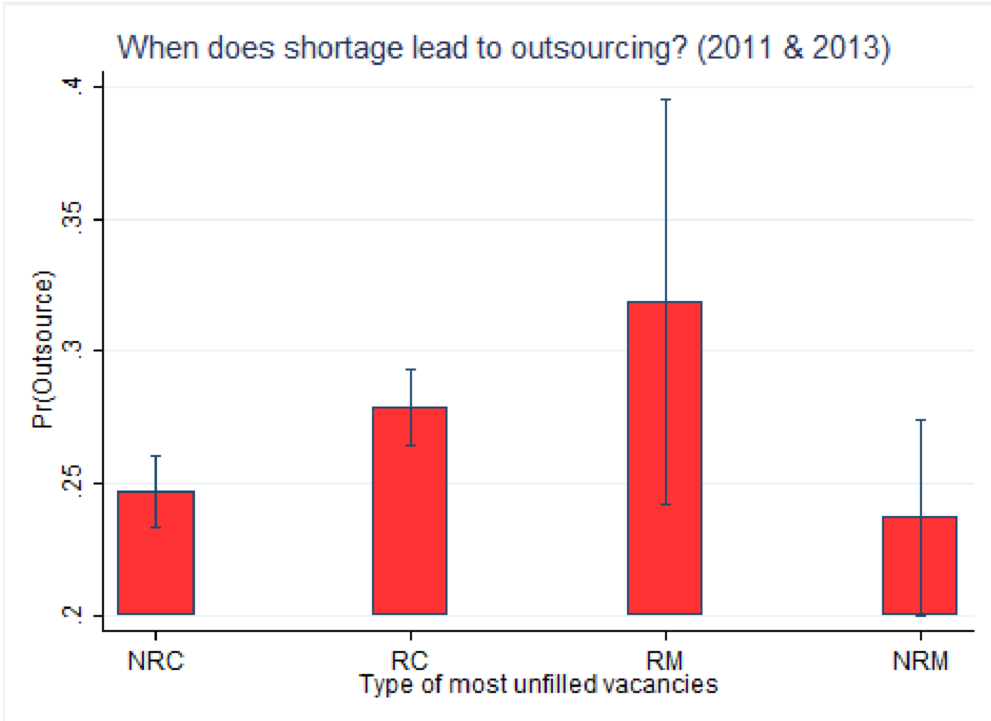
We first run the following probit regression.

$$Pr(\text{Outsource})_{i,t} = \alpha + \beta \text{ Firm Type}_{i,t} + \gamma X_{i,t} + \epsilon_{i,t}$$

Where $Outsource_{i,t}$ is a dummy equaling 1 if shortage would lead the firm to outsource. $Firm\ Type_{i,t}$ and $X_{i,t}$ are defined as before.

From Figure 10, we observe that irrespective of the type of shortage, all firms have a

Fig. 10. The effect of shortage type on the probability that the firm outsources



non-negligible probability of outsourcing. Also, while firms with shortage in routine occupations are more likely than firms facing shortage in non-routine occupations, this is only significant for firms with shortage in RC jobs (over firms with shortage in NRC jobs). Note that this question was only included in the 2011 and 2013 waves of the ESS.

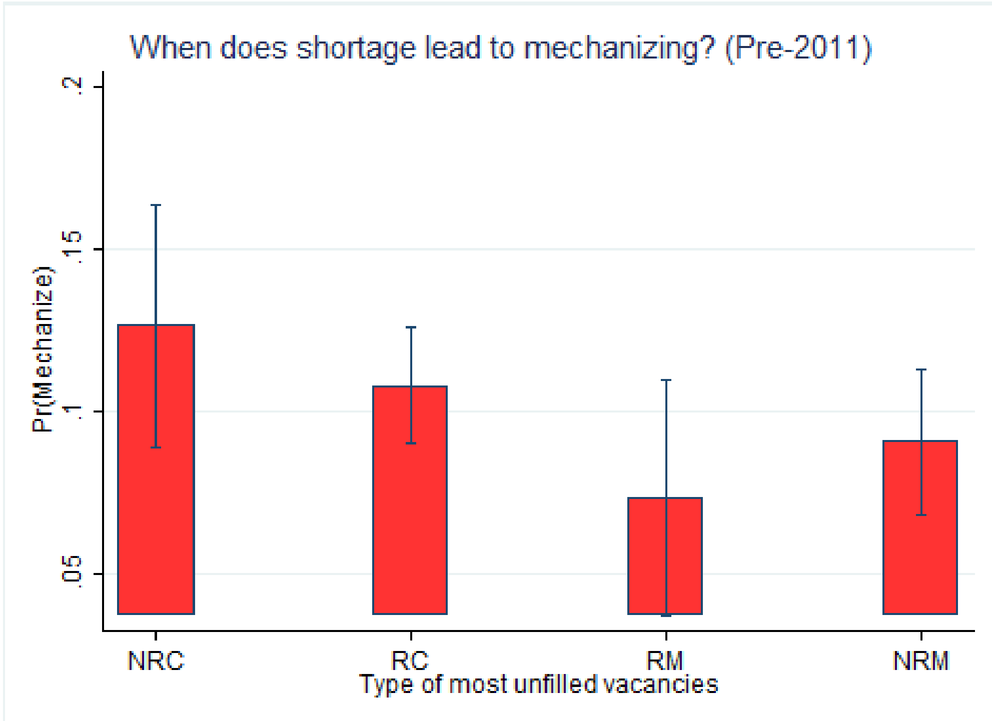
Concerning mechanization, we find that while firms facing all types of shortage have a non-zero probability of mechanizing, the magnitudes are rather low and there is no significant difference between routine and non-routine jobs. Note that this question was only asked in the 1999, 2001 and 2002 waves of the ESS. The regression run is

$$Pr(\text{Mechanize})_{i,t} = \alpha + \beta \text{ Firm Type}_{i,t} + \gamma X_{i,t} + \epsilon_{i,t}$$

Where $Mechanize_{i,t}$ is a dummy equaling 1 if shortage results in mechanization, where $Firm\ Type_{i,t}$ and $X_{i,t}$ are defined as before.

In short, the above results suggest that claims of shortage in routine jobs are not empty and they do seem to have concrete impacts on firm behaviour. In particular, shortage in the RM and RC occupation types are more likely to lead to shrinking and outsourcing respectively, which could account for why wages, hours worked and employment are not

Fig. 11. The effect of shortage type on the probability that the firm mechanizes



observed to increase in response to shortage for routine jobs.

4.4.3. Selective migration patterns

The last possibility we consider is that workers in routine jobs may for some reason be unable to move into pockets of higher shortage, which can explain why we do not observe any increases in wage or employment outcomes in areas with higher shortage. The LFS, though not a panel survey, does ask individual respondents about the region in which they lived and worked in the previous year. We run the following two regressions.

$$Pr(\text{Get a new job in a SP})_{i,t} = \alpha_0 + \alpha_1 Job_{i,t} + \beta X_{i,t} + \epsilon_{i,t}$$

and

$$Pr(\text{Get a new job in a SP} \mid \text{Change region})_{i,t} = \alpha_0 + \alpha_1 Job_{i,t} + \beta X_{i,t} + \epsilon_{i,t}$$

Where $Job_{i,t}$ is the current occupation type of individual i, and $X_{i,t}$ includes individual controls such as age, gender, marital status and education.

Figures 12 and 13 show that NRC workers are more likely to move to higher shortage regions than other worker types. What is more, even when considering only workers who did migrate to a different region, NRC worker-migrants are most likely to have moved into

Fig. 12. Probability that a worker in a particular occupation type migrates into a region with higher shortage

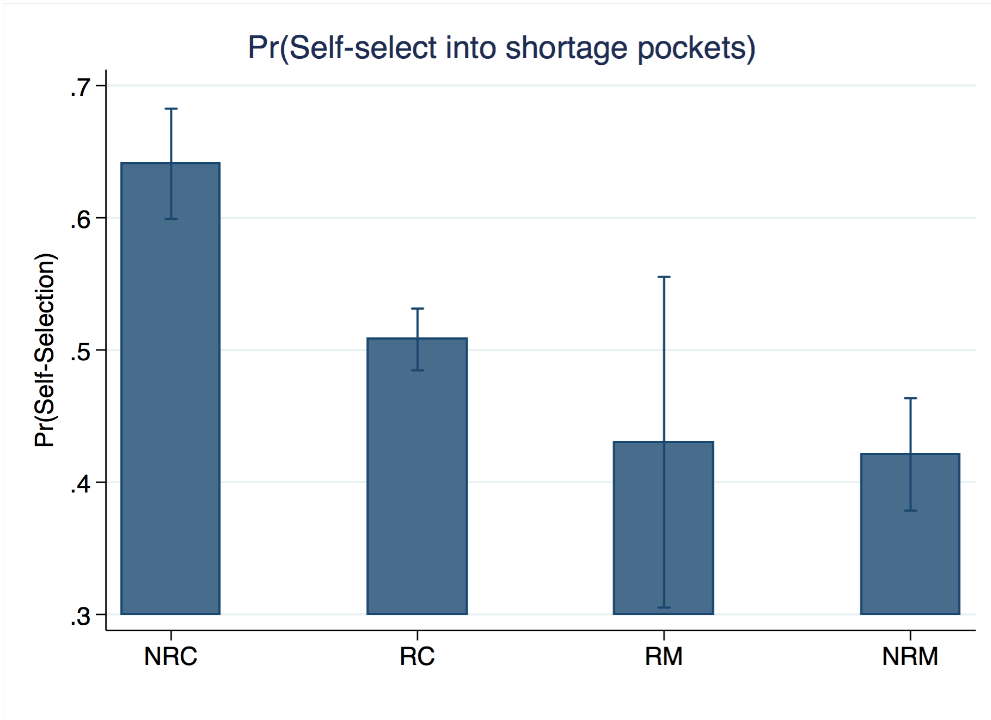
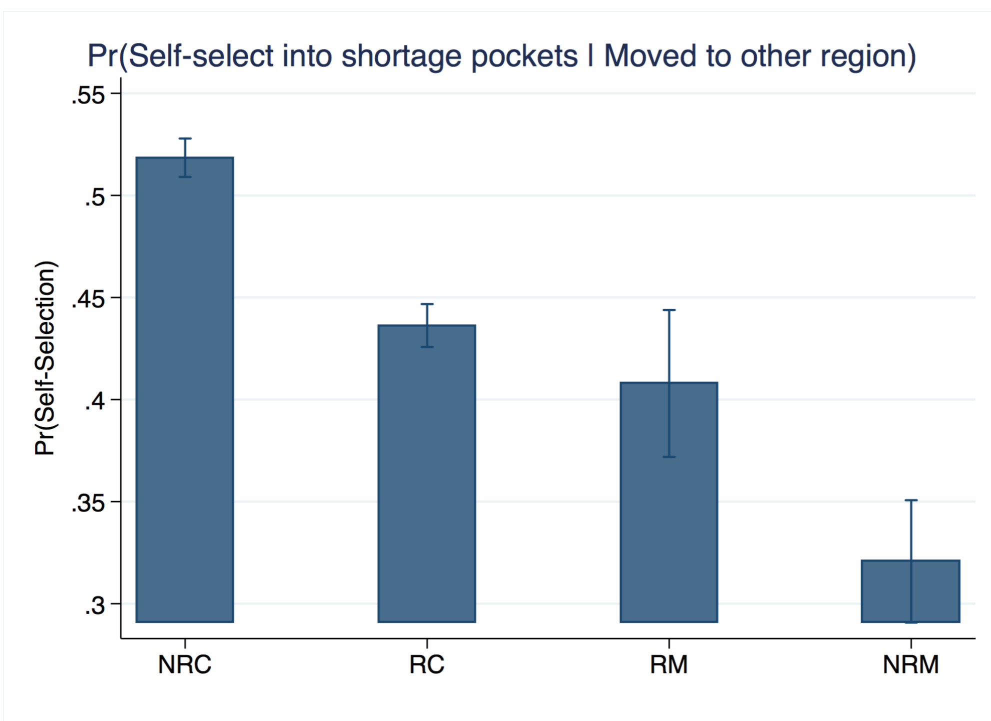


Fig. 13. Probability that a worker in a particular occupation type moves into a region with higher shortage given he/she migrates



a region with higher shortage in their occupation type. Hence, it seems that the differential rates of movement into higher shortage regions may play a role in the empirical findings, although it is hitherto unclear why non-NRC workers choose not to migrate to higher shortage pockets. Plausible reasons could be high fixed costs of migration or social transfers that mitigate the push and pull factors for migration, but these demand further investigation.

5. The Model

In this section, we build and estimate a search-and-matching model in order to understand (i) what drives occupational shortage, and (ii) why there are heterogeneous effects of shortage across occupations and markets, and (iii) who migrates towards higher shortage pockets. The model combines elements of a Diamond-Mortensen-Pissarides framework with models of directed search and wage posting as in Huckfeldt (2016), Guerrieri et al. (2017) and Rogerson et al. (2005).

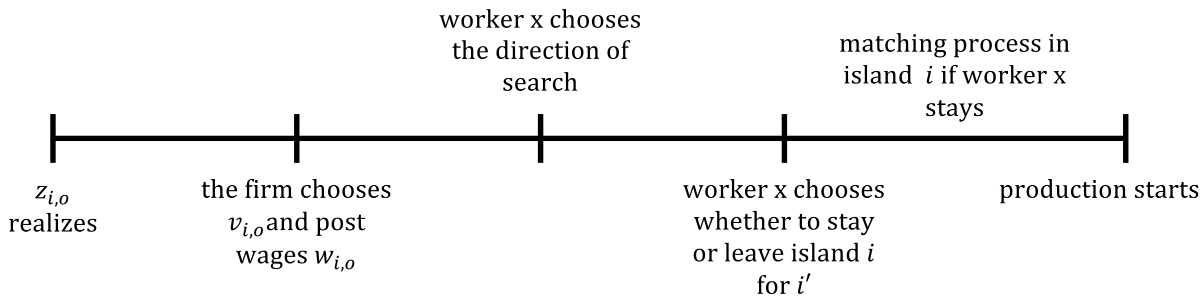
5.1. Set Up

Time is continuous. We imagine a world with a number I of "islands". Each island $i = \{1, 2, ..., I\}$ is a separate market inhabited by a unitary and infinitely-living mass of workers. Each worker is characterized by a skill-level x drawn from a uniform distribution $U_{[0,1]}$, and can be either unemployed or employed in a specific occupation. On each island i, there are two different occupations $o = \{1, 2\}$: the first occupation ($o = 1$) is skill-intensive, whereas the second one ($o = 2$) is skill-neutral. Moreover, within each island, occupations differ also in technology $z_{i,o}$ which follows a "island-specific" stochastic process over time. Given technology, firms endogenously choose the number of vacancy $v_{i,o}$ for each segment of the labor-market and post wages $w_{i,o}$. Given technology, the wages and the vacancy posted in each market, unemployed workers on island i direct their search only towards the sub-market with higher unemployment value. Upon deciding on their occupation, workers choose whether or not migrate to another island. If they do, they pay a moving cost. Then, the matching process in each submarket begins, with the new employed workers starting production at the beginning of the next period. Figure 5.1 represents the stylized time-line of the model for the i^{th}-island.

5.2. Productions, Technologies and Vacancies

There are two job-specific production functions:

Fig. 14. Time-line of Events



$$y_{i,1}(x, z_{i,1}) = z_{i,1}x \;\; ; \;\; y_{i,2}(x, z_{i,2}) = z_{i,2}.$$

Under this formulation, the production is skill-intensive in the first occupation, where a worker x has linear returns to his own skill-level. On the other hand, the production in the second job depends only on technology such that this job is skill-neutral.

Each technology follows a continuous-time AR(1) process of the form:

$$dz_{i,o} = -\rho z_{i,o}dt + \sigma_o dB_i$$

where dB_i is a standard-normal Brownian motion for island i. Despite heterogeneity in the innovation process across islands, we assume that the technology process $z_{i,o}$ has common standard deviation across all islands, i.e. $\sigma_{i,o} = \sigma_o, \forall i = \{1, 2, ..., I\}$ and $\forall o = \{1, 2\}$. Similarly, we assume that the persistence of the shock ρ is common across islands and occupations.

Given this, the value of production of a worker x when employed in occupation o on island i is:

$$rJ(x, z_{i,o}) = y_{i,o}(x, z_{i,o}) - w(x, z_{i,o}) - \delta \mathbb{E}_{z_{i,o}}\{J(x, z'_{i,o}) - V(z'_{i,o})\}$$

where r is the interest rate, δ is the exogenous separation rate, $w(x, z_{i,o})$ is the wage paid to the worker, and $V(z'_{i,o})$ is the value of posting a vacancy in the labor market o on island i. Similarly, vacancy posting evolves according to the following Bellman equation:

$$rV(z_{i,o}) = -c + m(\theta_{i,o})\mathbb{E}_{z_{i,o}}\{J(x, z'_{i,o}) - V(z'_{i,o})\}$$

where c is the cost of creating a vacancy, whereas $m(\theta_{i,o})$ is the probability for the firm on island i to fill a vacancy $v_{i,o}$. This probability is function of $\theta_{i,o}$, i.e. the job-specific market tightness on island i, and is expressed as follows:

$$m(\theta_{i,o}) = \frac{\psi(s_{i,o}^{\alpha})(v_{i,o}^{1-\alpha})}{v_{i,o}} = \theta^{-\alpha}$$

where ψ is the matching elasticity, α is the return on vacancy posting, and $s_{i,o}$ is the number of searchers in market o on island i.

5.3. Employment and Unemployment Value, and the Direction of Search

For a worker x employed in occupation o on island i, the value of employment is:

$$rN(x, z_{i,o}) = w(x, z_{i,o}) - \delta \mathbb{E}_{z_{i,o}}\{N(x, z'_{i,o}) - U(x, z'_{i,o'})\}$$

where $N(x, z'_{i,o})$ is the value of working in job o in the next period, and $U(x, z'_{i,o'})$ is the value of being unemployed in the next period and searching in market o', with o' not necessarily equal to the current o.

When an unemployed worker with skill-level x from island i searches in market o, his value of employment is:

$$rU(x, z_{i,o}) = b + q(\theta_{i,o})\mathbb{E}_{z_{i,o}}\{N(x, z'_{i,o}) - U(x, z'_{i,o'})\}$$

where b is the unemployment benefit, $q(\theta_{i,o}) = \theta_{i,o}^{1-\alpha}$ is the probability for an unemployed worker to fill a vacancy $v_{i,o}$. Again, $N(x, z'_{i,o})$ is the value of working in job o in the next period, whereas $U(x, z'_{i,o'})$ is the value of searching in market o' in the next period, with o' not necessarily equal to the current o. In fact, for a change in technology between two consecutive periods, the worker might want to change the direction of his search towards other jobs. This happens if and only if $U(x, z_{i,o'}) > U(x, z_{i,o})$. In other words, each period the worker solves the following problem to chose the direction of his search s:

$$o = \underset{s=\{1,2\}}{\text{argmax}}\{U(x, z_{i,1}); U(x, z_{i,2})\}$$

Hence, for each island i there exists a value $\hat{x}_i$ such that a worker with skill-level $x = \hat{x}_i$ is indifferent between searching for a skill-intensive or a skill-neutral job on island i. This argument leads to the following proposition.

Proposition 1. *On each island i, all workers $x > \hat{x}_i$ search for job $o = 1$ since $U(x, z_{i,1}) > U(x, z_{i,2})$, $\forall x > \hat{x}_i$. All workers $x \leq \hat{x}_i$ search for job $o = 2$ since $U(x, z_{i,1}) \leq U(x, z_{i,2})$, $\forall x \leq \hat{x}_i$.*

Proof. Since $o = 1$ is skill-intensive, the value of unemployment for a worker x searching in this market is increasing in his own skills, i.e. $\partial U(x, z_{i,1})/\partial x > 0$ and $\partial^2 U(x, z_{i,1})/\partial x^2 = 0$. On the contrary, since $o = 2$ is skill-neutral, the value of unemployment for a worker x searching in this market is independent of skills, i.e. $\partial U(x, z_{i,2})/\partial x = 0$. Therefore, $U(x, z_{i,1})$ is a linear and increasing function of x and intersects $U(x, z_{i,0})$ from below only once. This grants the existence and uniqueness of a value of $\hat{x}_i$ such that $U(x, z_{i,1}) > U(x, z_{i,2})$, $\forall x > \hat{x}_i$. □

In light of this, the equilibrium condition pinning down the direction of the search is the following:

$$U(\hat{x}_i, z_{i,1}) = U(\hat{x}_i, z_{i,2}) \ \ , \ \ \forall i = \{1, 2, ..., I\}. \tag{1}$$

5.4. *Choice of Migration*

Upon choosing occupation o on island i, a worker can decide whether or not to migrate to island i' and search for the same occupation. The worker pays moving cost $c(x)$ if he decides to move. Hence, the worker's choice of location l is such that

$$l = \underset{i \in I}{\text{argmax}} \{U(x, z_{i,o}); U(x, z_{i',o}) - c(x)\}$$

Therefore, for every occupation o on island i there will be a threshold $\tilde{x}_{i,o}$ such that the following holds:

$$U(\tilde{x}_{i,o}, z_{i',o}) - U(\tilde{x}_{i,o}, z_{i,o}) = c(\tilde{x}_{i,o}) \ \ , \ \ \forall o = \{1, 2\}, \ \ \forall i' \neq i. \tag{2}$$

The level of such a threshold depends on the functional form of $c(x)$. In fact, if $c(x) = c$, given the above stated properties of $U(x, z_{i,o})$, a fraction of workers searching in occupation $o = 1$, who satisfy $x \geq \tilde{x}_{i,1}$ will migrate. On the other hand, for workers searching in occupation $o = 2$, there will be a corner solution. Specifically, as long as $U(x, z_{i',2}) - U(x, z_{i,2}) \geq c$, all workers will migrate and $\tilde{x}_{i,2} = 0$. Otherwise, no worker will migrate since $\tilde{x}_{i,2} = \hat{x}_i$.

If c is a function of x, then an interior solution exists for both sectors. In other words, for both $o = \{1, 2\}$, there will be $\tilde{x}_{i,o}$ such that only workers with $x > \tilde{x}_{i,o}$ will migrate.

5.5. *Wage Posting*

Every employer of type $o = \{1, 2\}$ posts wages in order to maximize the probability that workers will search in sub-market o, i.e. in order to increase the value $U(x, z_{i,o})$, $\forall x$. Since the employer cannot choose technology, the only channel through which he can raise the wage and influence search behavior is through the job-specific market tightness $\theta_{i,o}$. This translates into the following problem for every employer of type o on island i:

$$\max_{\theta_{i,o}} \mathbb{E}_x\{U(x, z_{i,o})\}$$

such that the equilibrium condition for job-specific market tightness simply is:

$$\frac{\partial \mathbb{E}_x\{U(x, z_{i,o})\}}{\partial \theta_{i,o}} = 0 \ , \ \forall o = \{1, 2\} \text{ and } \forall i = \{1, 2, ..., I\}. \tag{3}$$

5.6. *Employment Dynamics*

The evolution of employment in each sub-market o on each island i is:

$$\frac{\partial n_{i,o}}{\partial t} = s_{i,o} q(\theta_{i,o}) - \delta n_{i,o} \tag{4}$$

i.e. the time-change of the employment stock in occupation o on island i is equal to the flow of workers from unemployment to job o ($s_{i,o} q(\theta_{i,o})$) net of workers who lost their jobs due to exogenous displacement ($\delta n_{i,o}$).

5.7. *The Equilibrium*

Under this set-up, now we define the equilibrium condition for the economy.

Definition 1. *Conditional on the stochastic technological process $z_{i,1}$ and $z_{i,2}$, the equilibrium for the economy is a vector $\{\theta_{i,o}, n_{i,o}, \hat{x}_i, \tilde{x}_{i,o}\}_{t=0}^{\infty}$ satisfying equations (1)-(4) for each occupation $o = \{1, 2\}$ on each island $i = \{1, 2, ..., I\}$.*

We can now proceed by describing how we estimate the model. Thereafter, we show simulations using the estimated parameters in order to understand the mechanics of the model, how shortage affects wages and employment and under which conditions the model generates the comovements observed in the data.

6. Model Calibration

In this section, we bring the model to the data. Instead of considering four different occupations, as in the empirical part of this paper, we reduce our analysis only to two jobs: (i) non-routine jobs i.e. the sum of non-routine cognitive and non-routine manual jobs, and (ii) routine jobs i.e. the sum of routine cognitive and routine manual jobs. For these two major groups, we build time-series for employment, wages and shortage at regional-industrial level. Then we calculate the average correlation of wages and employment with respect to shortage, and the average employment rate for non-routine occupations and its variance across markets. Once we collect these moments from the data, we move to the estimation.

First of all, we preset some parameters with standard values from the literature: $r = 0.015$, $b = 0.4$, $\delta = 0.1$, $c = 0.2$ and $\rho = 0.95$ as in Shimer (2005); $\alpha = 0.5$ and $\psi = 1$ as in Petrongolo and Pissarides (2001). For simplicity, we set $z_{i,2} = 1$ for all islands $i = \{1, 2, ..., I\}$, whereas we allow $z_{i,1}$ to differ across islands. Finally, we assume that there are 100 islands, i.e. $I = 100$, and that technologies in the two occupations are shocked for 200 consecutive periods. The list of preset parameters is given in Table 9.

Table 9: Preset Parameters

Parameter	Description	Value
r	Interest rate	0.015
b	Value of leisure	0.40
δ	Separation rate	0.10
c	Vacancy cost	0.20
α	Matching elasticity	0.5
ψ	Matching efficiency	1
$z_{i,2}$	Skill-neutral tech.	1
ρ	Shock persistency	0.95

Second, we assume $z_{i,1} \overset{i.i.d}{\sim} N(\mu_{z_1}, \nu_{z_1})$, i.e. the technology of the skill-intensive occupation is on average equal to μ_{z_1} across islands, and the dispersion of such productivity is equal to ν_{z_1}. Finally, we assume quadric moving costs, i.e. $c(x) = \frac{1}{2}(\kappa - x)^2$. Therefore, the unknown parameters of the model are μ_{z_1}, ν_{z_1}, σ_1, σ_2 and κ, and we estimate them by simulated method of moments. In particular, we use the average employment rate for non-routine jobs and its standard deviation across region-industry cells to estimate the mean productivity of non-routine jobs μ_{z_1} and its standard deviation ν_{z_1} across all I islands. Then we use the correlation of wages and employment with respect to shortage for each occupation, to back up the volatility σ_1 and σ_2 of the stochastic technological process over time. The fraction of movers across region-industry cells identifies κ. Therefore, there are 7 moments for 5 unknown parameters. The list of estimated parameters is given in Table 10, while the list of targeted moments with the model and data values and the corresponding test statistics is given in Table 11.

Table 10: Calibrated Parameters

Parameter	Description	Value
μ_{z_1}	Mean skill-intensive tech.	1.940
ν_{z_1}	Skill-intensive tech. dispersion	0.046
σ_1	Std. for skill-intensive shocks	0.110
σ_2	Std. for skill-neutral shocks	0.0001
κ	Cost function param.	2.473

Table 11: Targeted moments and model moments

Moment	Data	Model	Test stat.
$\overline{n}_1$ across islands	0.56	0.54	4.97
$Std(n_1)$ across islands	0.03	0.02	19.71
$Corr(n_1, Shortage_1)$	0.18	0.12	1.83
$Corr(n_2, Shortage_2)$	0.05	0.01	0.18
$Corr(w_1, Shortage_1)$	0.09	0.15	2.22
$Corr(w_2, Shortage_2)$	0.01	0.005	0.07
Sh. of movers across islands	0.042	0.045	6.56

From Table 10, notice that skill-intensive technology is on average almost twice more productive than skill neutral technology ($\mu_{z_1} = 1.94$) across islands. The dispersion across islands of such productivity is relatively small ($\nu_{z_1} = 0.046$), i.e. the level of skill-intensive technology does not vary much across islands. The parameter characterizing the moving-cost function is high ($\kappa = 2.473$), thus allowing only few workers to move across islands. The standard deviation of the stochastic technological process is way higher in the skill-intensive market ($\sigma_1 >> \sigma_2$).[5] This is key to explain the uneven adjustments to shortage across jobs and markets as observed in the data. In fact, from Table 11, this parametrization leads to positive and significant correlations of employment and wages only in the skill-intensive occupation such that the model is consistent with the results from the empirical part of this paper (Section 4). Moreover, this parameterization sheds light on which type of technological change is needed to generate correlations close to the ones observed: in fact, with $\sigma_1 >> \sigma_2$, i.e. with the skill-intensive market being relatively more volatile, the skill-intensive technology will always react more to a shock. Hence, technological shocks are always biased towards this market. This is what we mean by SBTC.

In the next section, we develop the argument on SBTC by running impulse responses functions (IRFs) under the estimated parametrization and discuss the mechanics of the model. Then we run some counterfactuals to show that SBTC is necessary for the model to stay close to the data. Finally, we discuss the skill distribution of migrants across islands.

7. Discussion

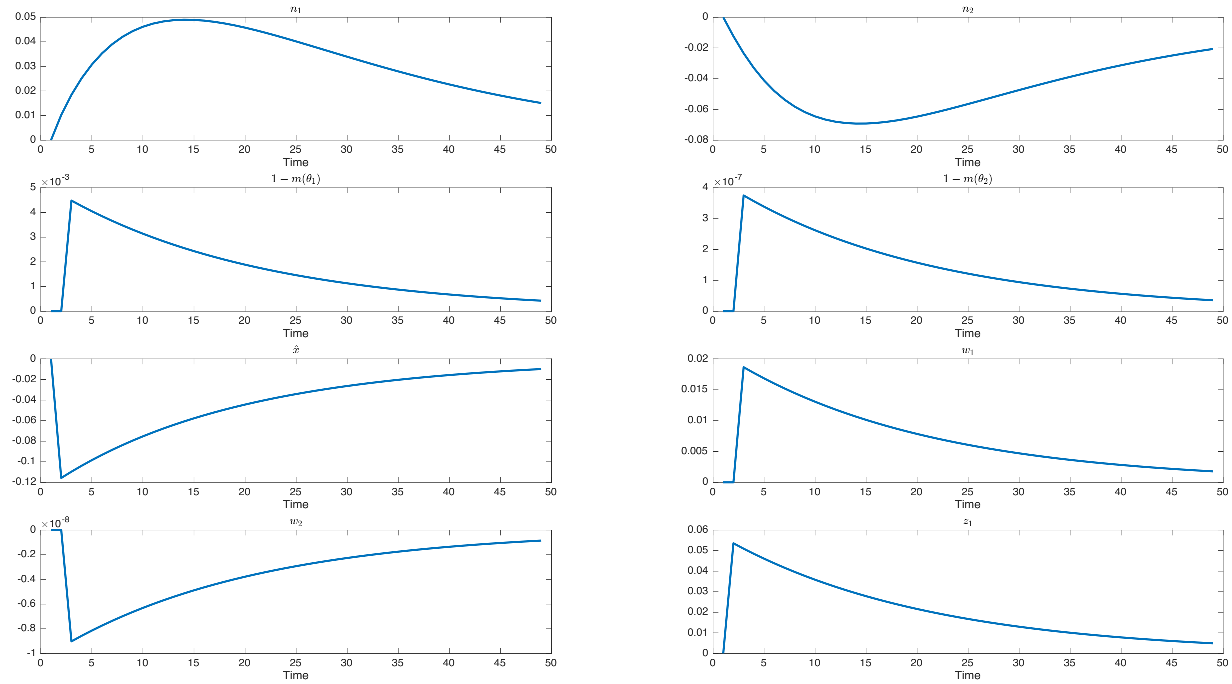
7.1. IRFs and Model Mechanism

Here, we plot impulse responses for the "average-island", i.e. an island with $z_{i,1} = \mu_{z_1}$. First of all, we show how the average economy reacts to a 1-standard-deviation shock in each segment of the labor market separately. Then we repeat the exercises by shocking technology in both segments at the same time.

Consider first Figure 15. Here we consider a one single positive shock on z_1. On impact, technology increases by σ_1 in the skill-intensive segment of the labor market. This generates an immediate rise in vacancy posting in this market, i.e. firms post more vacancies in the market that has suddenly become more productive. Such vacancy posting behavior leads to an increase in the share of unfilled vacancies ($1 - m(\theta_1)$) so that shortage increases as well,

[5] In Appendix C we show the shape of the loss function.

Fig. 15. IRFs for a z_1 shock



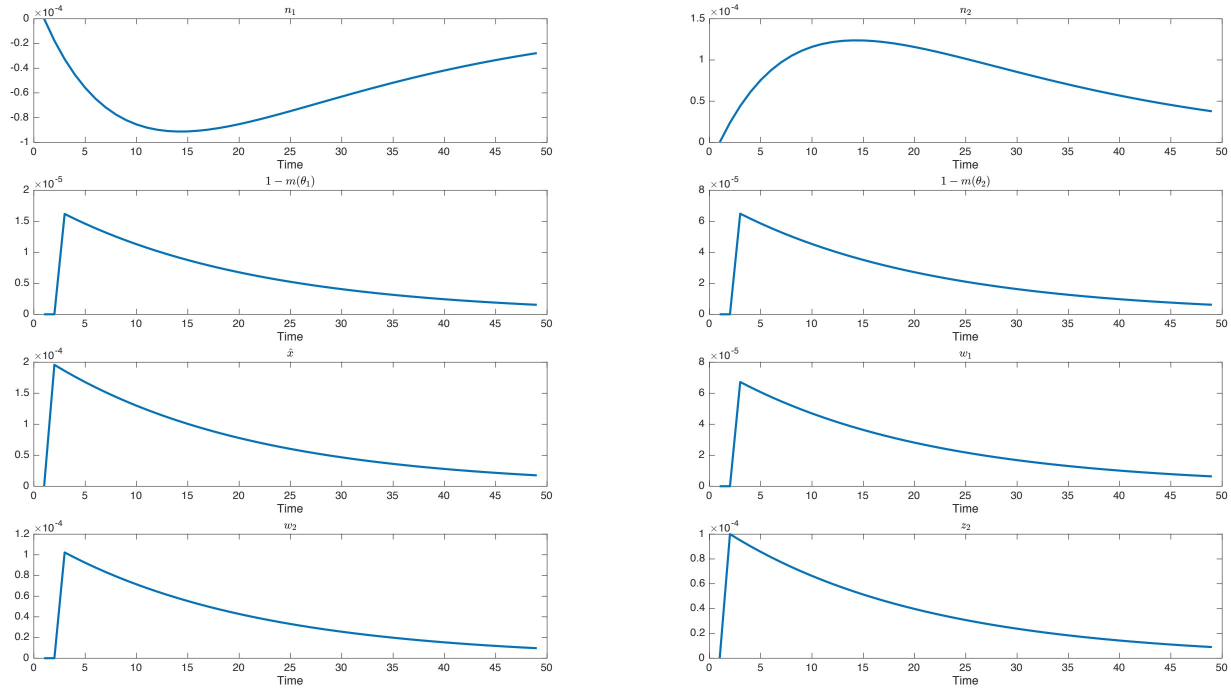
i.e. firms find it hard to fill the posted vacancies. As a reaction firms post higher wages in order to attract more workers into this market. The increase of w_1 is large enough to change the direction of the search for many workers. In fact, $\hat{x}$ falls by 12%, i.e. more workers search in the skill-intensive market. As a consequence, employment in the skill-intensive sector rises. The dynamics in the skill-neutral sector are different. First of all, due to the fact that now more workers are searching somewhere else, the lower-tier market experiences some shortage as well, but for different reasons. Employers in this segment post just a few vacancies to try to maintain the stock of incumbent workers. For this purpose they also raise wages, but not as much as in the skill-intensive job. Yet, the net effect is negative and the stock of employment in the skill-neutral market still falls.

To sum-up, for a SBTC shock, the model generates a positive correlation of wages and employment with shortage only in the skill-intensive market.

Consider now Figure 16. Here we consider a one single positive shock on z_2. Now, the result is opposite to the SBTC case: shortage and wages increase more than proportionally in the skill-neutral sector so to attract more workers and increase the stock of employment here.

Finally, consider the case in which both jobs benefits from a technological shock at the same time. Which effect prevails? The fact that the skill-sensitive market is more sensitive

Fig. 16. IRFs for a z_2 shock



to shocks than the skill-neutral one, means that the effects of SBTC prevail. Figure 17 shows results for this scenario.

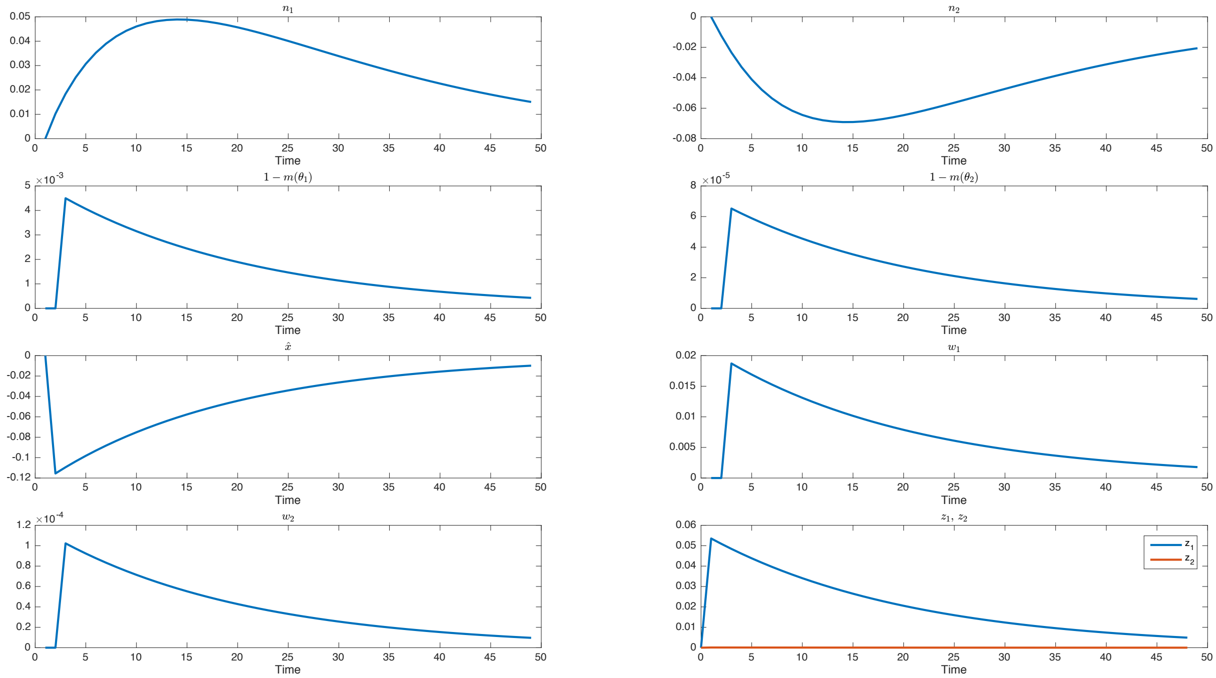
In light of this analysis, we conclude that SBTC must be the prevailing technological process across islands and over time. This is consistent with the literature on job and wage polarization and SBTC as in Acemoglu (2002), Autor (2007), Acemoglu and Autor (2011b) where they show that it is an unbalanced technological change that causes the increase of vacancy posting and salaries in non-routine occupations, job and wage polarization. This theoretical part builds on this and shows that the main driver of shortage and the uneven adjustment of labor markets to shortage is indeed skill-biased technical change.[6]

7.2. The Skill-Distribution of Migrants and Frequency of Migration Flows

The world we described so far is characterized by I separate islands. Each of them differs from the others on the level of skill-intensive technology $z_{i,1}$ and the stochastic technological processes $dz_{i,o}$. This heterogeneity is the determinant of migration flows across islands. However, the possibility of migrating is limited by the capacity of each worker to pay moving cost $c(x)$. In this section, we study the role of skills in determining migration. By running

[6]See Appendix D for the case in which both technologies change by the same amount when hit by a shock.

Fig. 17. IRFs for a z_1 and z_2 shock



a simulation across all I islands for 200 periods, we backup (i) the frequency of islands experience migration outflows and the skill-distribution of migrants in these islands.

Consider the left-panel of Figure 18. Here we plot the frequency of islands experiencing migration outflows over the minimum skill-level required in those islands in order to move and cover the moving-cost. Out of our simulation, only 4.5% of our sample experienced migration flows. In those cases, migrants are coming from the top of the skill distribution. In fact, in 2% of islands, the skill-level of migrants lies within the $[0.8 - 0.9]$ bin, while in the other 2.5% of islands, it falls within the $[0.9 - 1.0]$ bin. In other words, there is only a small share of islands experiencing migration outflows. Within these islands, most of the time, migrants belong to the top percent decile of the skill distribution.

When considering the probability for workers to migrate (Figure 18, right panel) over the minimum skill-level, we see that the probability is declining with the minimum skill threshold: the lower the threshold $\tilde{x}_{i,o}$, the higher the probability for workers to migrate. But, as explained above, most of the time migrants come from the top percent decile, meaning that there are very few migrants in the entire economy and that they come from the top of the skill-distribution.

Finally, since migrants have such high skills, they (almost) always search for skill-intensive

Fig. 18. Migration Flows and Skill Distribution

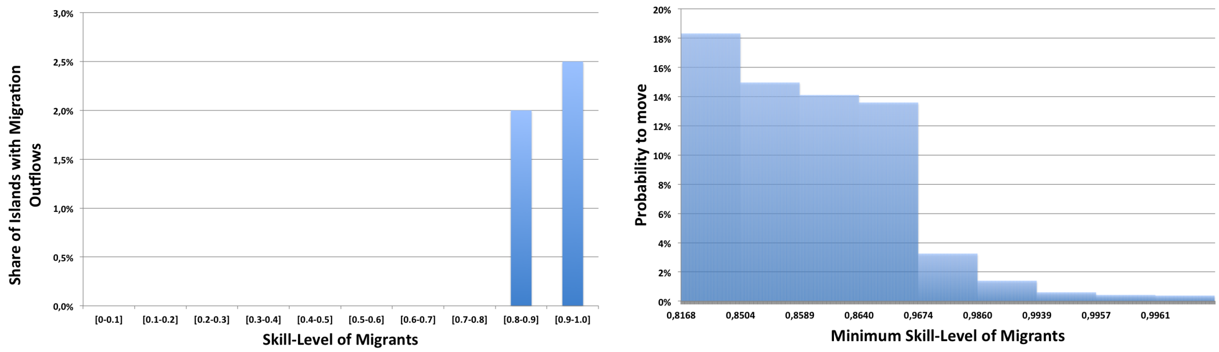
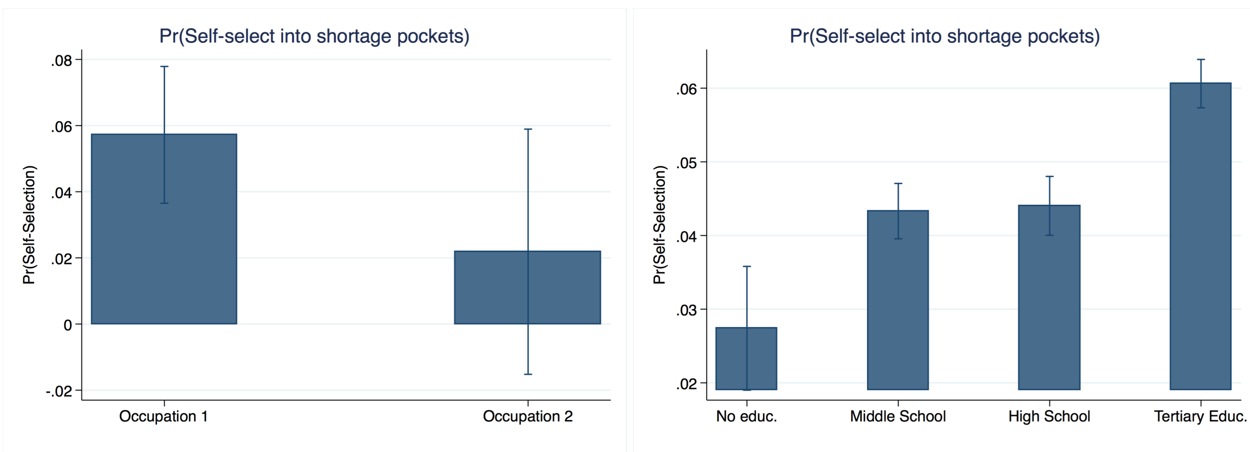


Fig. 19. Which jobs do migrants get? What is their education?



job. In this sense, migrants are most of the times very skilled, they searcher for a skill-intensive job and, if they can, they self-select in shortage pockets where salaries are higher and job opportunities bigger. This prediction of the model is in line with what we observe in the data. Consider the probability of moving into shortage pockets (islands) as a function of the job workers obtained by migrating, as shown in the left panel of Figure 19. 6 % of workers in self-select into higher shortage pockets in occupation 1, significant at the 5 percent level. On the other hand, only a insignificant 2% moves for occupation 2. When we study the same probability as a function of education -a proxy for skills in the model- we see that it is always workers with a tertiary education degree that are most likely to move and self-select into shortage pockets.

8. Conclusions

In this paper, we have discussed the existence and incidence of occupational shortage, as well as the resultant labor market adjustments. Adopting a measure of shortage given by the number of hard-to-fill vacancies in the Employer Skills Survey conducted in the UK, we show that wages increase in response to labor market shortage only in non-routine jobs, leading to an eventual increase in employment, while no such response is observed in routine jobs. This finding is robust to different empirical strategies and levels of aggregation.

Examining the reasons for the discrepancy between routine and non-routine jobs, we find no evidence that there is systemic over-reporting of shortage for routine jobs by human resource managers relative to that for non-routine jobs. Instead, this empirical finding seems to be in line with the secular decline of routine jobs, which has been also cited as one of the driving forces behind job polarization. The secular decline of routine jobs leads to the relative fall in wages and the exit of workers from this sector, thereby increasing the difficulty with which such jobs are filled.

The stylized theoretical model presented in this paper confirms this initial intuition. Characterizing local labor markets by their broad occupation type - routine and non-routine, as well as by location, this paper has demonstrated how SBTC can account for the different responses of routine and non-routine occupations to shortage. While having previously been shown to account for the decline in wages and employment in routine occupations, SBTC can also be behind the routine sector's inability to mitigate shortage. Moreover, the model also makes predictions on the migration patterns of workers into shortage pockets that are in line with the data. Highly-skilled workers, most often affiliated to the non-routine occupation, are most likely to migrate into pockets of higher shortage. The extent to which these differences in shortage adjustments and mobility patterns accelerate the decline of the routine sector warrants further study.

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Appendix A. Further empirical details

A.1. More descriptive statistics

Figure A.1 shows the evolution of shortage share from 1999 to 2013 over the 9 administrative regions of England for each occupation category. In the long run, from 1999 to 2013, shortage declines across all regions and all 4 occupations. Yet, substantial variation exists across local labor markets. For NRC jobs, for instance, shortage has declined the least in London, the East of England and the South East, while declining far more in Yorkshire and the Humber, the North East, North West and the West Midlands. In contrast, for RC jobs, shortage has decreased the least in the North West, West Midlands, as well as London. Despite the overall long run declining trend, there is substantial variation in shortage changes between regions, as well as in the short run. We exploit this variation across local labor markets later in the subsequent empirical strategy.

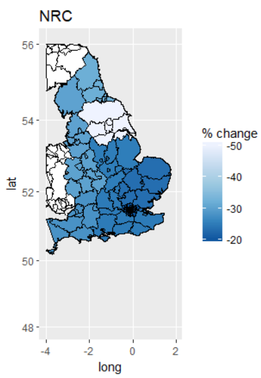
Figure A.2 gives the overall shortage change by industry over time from 1999 to 2013 separately for each occupation. Observe that within each occupation category, there is some heterogeneity in shortage share changes across industries. For NRC jobs, while most industries experienced a decline in shortage share from 1999 to 2013, Mining, Manufacturing and Public Administration faced an increase in shortage share. For RC jobs, shortage share for all industries decreased during the time period except for Education. On the contrary, for RM jobs, half of the industries had an increase in shortage share and the other half experienced a decrease. Lastly, for NRM jobs, only Transport and Finance faced a rise in their shortage shares.

A.2. The role of firm-specific characteristics

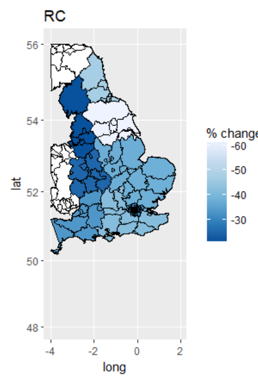
It is also possible that instead of a distinction between routine and non-routine jobs, it could be that firms that have more routine vacancies are somehow less able to fill their vacancies. Otherwise put, the empirical findings could be due to firm-specific characteristics instead of occupation-specific ones. As such, examining whether firms with multiple hard-to-fill vacancy types treat routine and non-routine types of shortage differently would be helpful in ruling out (or not) this hypothesis.

Figure A.3 shows the variety of vacancies among small, medium and large firms[7]. Variety equals 1 if, for example, the firm only has NRC vacancies and equals 4 if the firm has unfilled

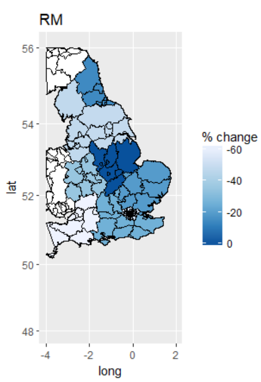
[7] A small firm is defined as one with between 5 to 49 employees, a medium firm between 50 and 249 employees and a large firm 250 employees and above.



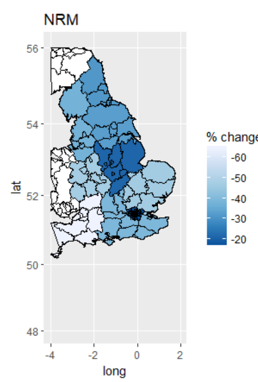
(c) Non-Routine Cognitive



(d) Routine Cognitive

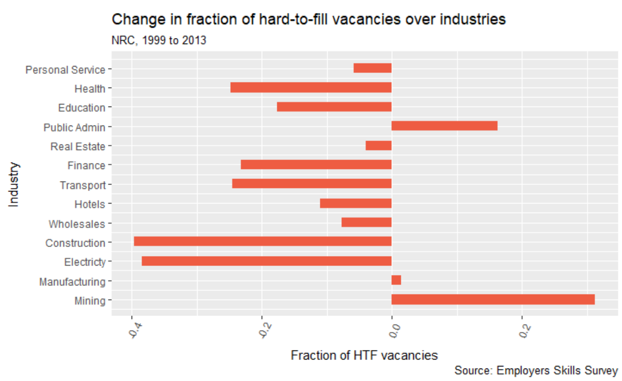


(e) Routine Manual

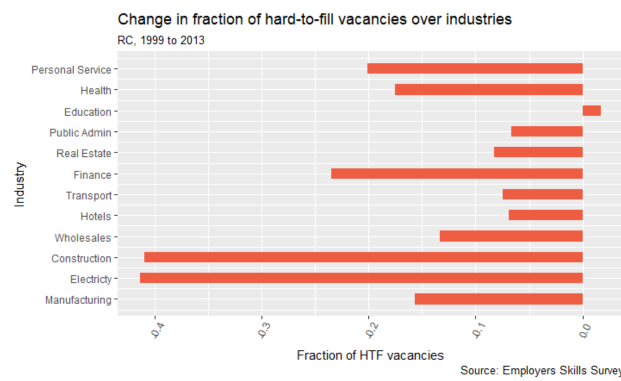


(f) Non-Routine Manual

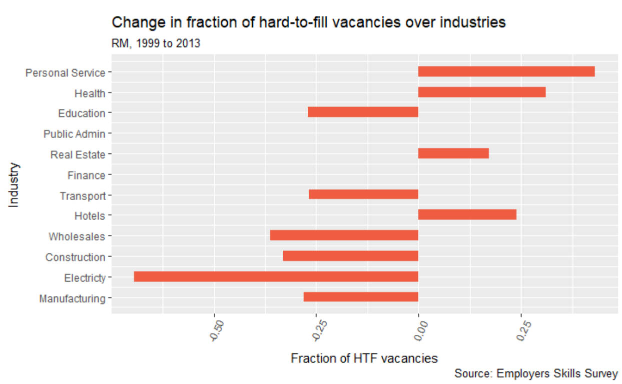
Fig. A.1. Overall change in shortage share by region and occupation category between 1999 and 2013



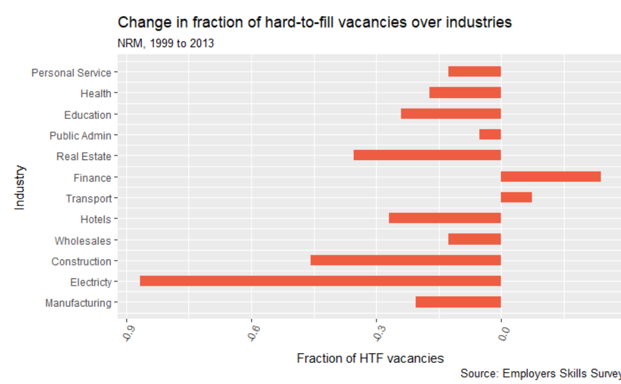
(a) Non-Routine Cognitive



(b) Routine Cognitive



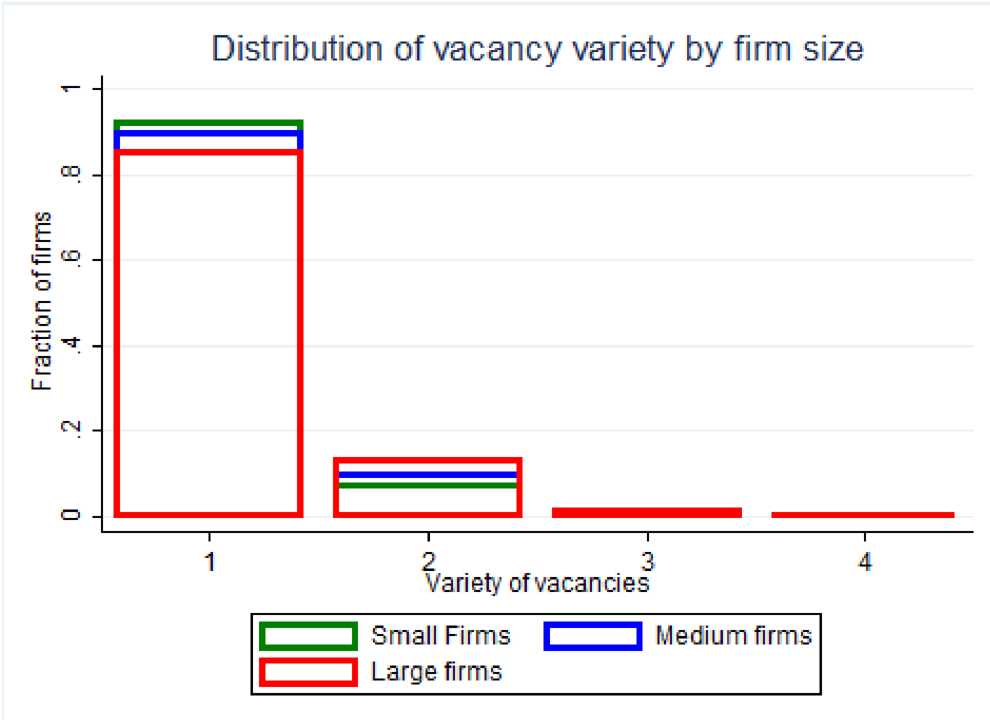
(c) Routine Manual



(d) Non-Routine Manual

Fig. A.2. Evolution of shortage share by industry and occupation category between 1999 and 2013

Fig. A.3. The variety of vacancies posted by each firm



vacancies in all 4 job types. We observe that firms report unfilled vacancies in only 1 job type, meaning the distinction between firm effects and effects of vacancy types is moot. Hence, this hypothesis cannot be further discussed.

Appendix B. Bartik Instrument: 1st Stage

Here we report the first-stage regressions for the 2SLS estimation described in Section 4.1. Table 12, 13, 14 report results for the three dependent variables (wages, hours worked and probability of employment) in each occupation.

As is evident, the instrument is strong enough when instrumenting our shortage measure for NRC and NRM jobs. On the contrary, the Bartik instrument is weak (but still significant) for RC and RM occupations.

Appendix C. The Loss-Function

As discussed in Section 6, we estimate the model by simulated method of moments, i.e. we minimize the following loss-function:

Table 12: Shortage and Wages (1st stage)

	(1) $\Delta Shortage^{NRC}$	(2) $\Delta Shortage^{RC}$	(3) $\Delta Shortage^{RM}$	(4) $\Delta Shortage^{NRM}$
Bartik Shock	0.0993^{***}	0.109^{**}	0.160^{*}	0.416^{**}
	[0.026]	[0.049]	[0.086]	[0.185]
$FE\ (reg, ind, wave)$	Yes	Yes	Yes	Yes
$Controls$	Yes	Yes	Yes	Yes
N	13031	10673	2931	9275
R^2	0.237	0.137	0.181	0.141

t statistics in brackets; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Shortage and Hours (1st stage)

	(1) $\Delta Shortage^{NRC}$	(2) $\Delta Shortage^{RC}$	(3) $\Delta Shortage^{RM}$	(4) $\Delta Shortage^{NRM}$
Bartik Shock	0.103^{***}	0.0384^{*}	0.157^{*}	0.525^{***}
	[0.026]	[0.021]	[0.092]	[0.188]
$FE\ (reg, ind, wave)$	Yes	Yes	Yes	Yes
$Controls$	Yes	Yes	Yes	Yes
N	17674	1784	1132	2606
R^2	0.244	0.135	0.181	0.109

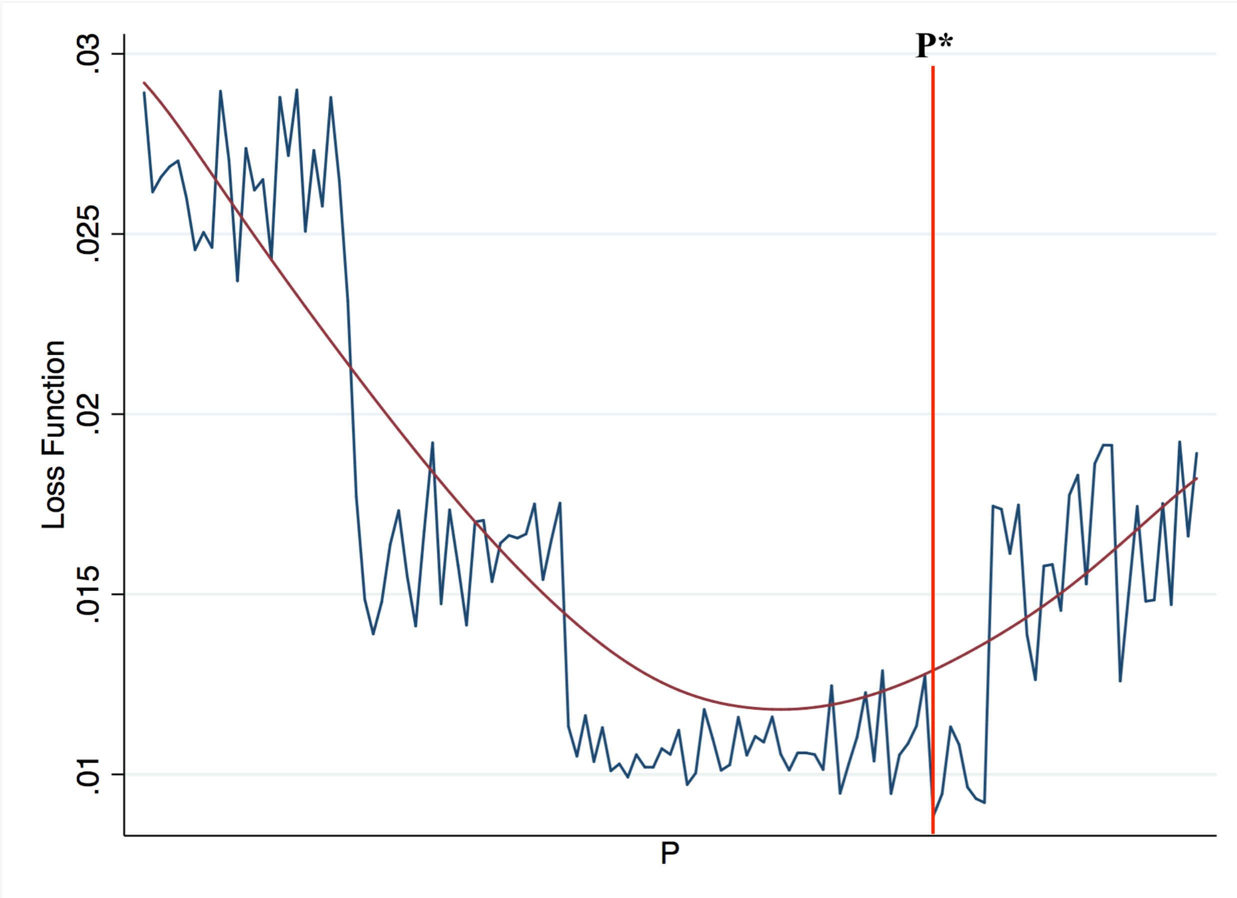
t statistics in brackets; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Shortage and Employment Pr. (1st stage)

	(1) $\Delta Shortage$
Bartik Shock	0.0509^{**}
	[0.022]
$FE\ (reg, ind, wave)$	Yes
$Controls$	Yes
N	74018
R^2	0.110

t statistics in brackets; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Fig. C.4. Calibration



$$L(P) = [m - m(P)]'W[m - m(P)]$$

with W being an identity matrix, m is vector of observed moments and $m(P)$ is the vector of moments generated from the vector of parameters $P = [\mu_{z_1}, \nu_{z_1}, \sigma_1, \sigma_2]$. In order to minimize this function, our algorithm develops in three steps: first, we build a grid of points in the parameter space; then, for every combination of points, we simulate 100 separate economies (islands) for 200 hundred periods and collect moments for each one. Finally, we average out the moments across islands and build the loss-function L(P).

Figure C.4 plots the loss-function aver a grid of values in the parameter space $\mathbb{R}^4$. This function is convex in the $\mathbb{R}^4$ space and has minimum at $P^* \in \mathbb{R}^4$.

Appendix D. Same Technology Change across Markets

In Section 7, we discussed the effect of technological change when a shock hits a segment of the labor market at different intensity, i.e. when $\sigma_1 \neq \sigma_2$. Here, we want to study the effects of a shock that impact both technologies $z_{i,1}$ and $z_{i,2}$ in the same way. Specifically, we consider the scenario in which both technology becomes 5% more productive when a shock hits. Given the estimated average level across island $\mu_{z_1} = \bar{z}_1 = 1.94$, and $z_{i,2} = 1$ across all islands I, this is equivalent to imposing $\sigma_1 = 0.097$ and $\sigma_2 = 0.05$. Figure D.5 plots the Irfs for this case. As evident, variables comove across markets when technologies change by the same amount. However, there are some facts to highlight. First, wages react in the same way to the shock i.e. they increase both by 5%. Second, although the same wage adjustment, there are more workers looking into the skill-intensive market, where they can have a higher salary (in level) and a higher return to skills. Third, skill shortage increases in both markets, but -due to the change in the direction of the search for some workers- the skill-neutral market experiences larger occupational shortage. Finally, as a consequence to all of this, employment increases more in the skill-intensive market when the shock hits, and the employment dynamic is way more persistent here than in the skill-neutral market.

To sum up, for a common technological shock across jobs, firms adjust wages upward by the same amount. Yet, the skill-intensive market is able to attract more workers such that it is able to persistently hire more workers than the skill-neutral one. In other words, a common technology shock makes the wage-posting channel irrelevant. It is purely the different return to skills across sectors that explain the uneven adjustments in terms of employment.

Fig. D.5. IRFs: same tech. change across markets