Understanding sectoral differences in downward real wage rigidity: workforce composition, institutions, technology and competition

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Abstract

This paper examines whether differences in wage rigidity across sectors can be explained by differences in workforce composition, competition, technology and wage-bargaining institutions. We adopt the measure of downward real wage rigidity (DRWR) developed by Dickens and Goette (2006) and rely on a large administrative matched employer-employee dataset for Belgium over the period 1990-2002. Firstly, our results indicate that DRWR is significantly higher for white-collar workers and lower for older workers and for workers with higher earnings and bonuses. Secondly, beyond labour force composition effects, sectoral differences in DRWR are related to competition, firm size, technology and wage-bargaining institutions. We find that wages are more rigid in more competitive sectors, in labour-intensive sectors, and in sectors with predominant centralised wage-setting at the sector level as opposed to firm-level wage agreements.

Keywords: wage rigidity, matched employer-employee data, wage-bargaining institutions
JEL code: J31

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The opinions expressed in this paper are solely our own and do not necessarily reflect the opinion of the National Bank of Belgium. Our thanks to W. Dickens for providing us with the International Wage Flexibility Project (IWFP) estimation programmes. We also thank CIMIRe, the Datawarehouse Labour Market of the Belgian Social Security System and Statistics Belgium for giving us access to the individual datasets. We are also grateful to participants of the WDN meetings and our colleagues for fruitful discussions. The paper was prepared while Ladislav Wintr was working at the National Bank of Belgium.

Non-technical summary

Economic theory has highlighted the role that wage rigidity has to play in labour market outcomes as well as its influence on the conduct of monetary policy. Wage rigidity has been pointed up as a factor of large employment fluctuations and a source of unemployment. In addition, it has been shown that wage rigidity and price stickiness generate inflation inertia and persistence of output fluctuations, which, in turn, introduces a trade-off between inflation volatility and output variations. In such a framework, pure inflation targeting is no longer the optimal monetary policy. Rather, the objective of monetary authorities should be to reduce the volatility of both inflation and unemployment simultaneously.

Given the importance of wage rigidity for macroeconomic outcomes, a many research papers aim at evaluating the degree of wage rigidity. By contrast, there is much less investigation into the sources of wage rigidity. These can be assessed by comparing countries, sectors or groups of workers with different degrees of wage rigidity. Previous research findings suggest that differences in wage rigidity across countries may be related to differences in the degree of unionisation, collective bargaining coverage, employment protection legislation, centralisation and coordination of wage bargaining. Further, differences in wage rigidity across sectors have been attributed to the percentage of blue-collar workers in the sector and to capital intensity.

This paper contributes to this question by examining the factors explaining differences in wage rigidity across workers and across sectors. First, we estimate downward real wage rigidity (DRWR) for workers in different occupations, age categories and sectors, and examine differences across worker categories. Second, we estimate DRWR by sector and investigate the role of workforce composition, competition, technology, firm size and centralisation of wage bargaining in explaining differences in wage rigidity across sectors.

Our analysis is based on a large administrative employer-employee dataset for Belgium for the period 1990-2002. We consider manufacturing industries as well as services and construction. We disregard agriculture, extraction and non-market services, and firms with less than five employees.

We estimate wage rigidity following the methodology developed by the International Wage Flexibility Project and described in Dickens and Goette (2006). Downward real (nominal) wage rigidity is defined as the fraction of workers who would receive a real (nominal) wage freeze if they were due for a real (nominal) wage cut. Given that Belgium is characterised by high DRWR and very low DNWR, consistent with full automatic indexation, we focus on real rigidity.

Our results point to substantial differences across workers and sectors. DRWR is 10 percent higher for white-collar workers than for blue-collar workers. This may be explained by the fact that both hiring costs and the risk of shirking are higher for white-collars workers, and also by the fact that, in Belgium, most white-collar workers have automatic age-related pay rises. In addition, DRWR tends to be higher for younger workers, possibly because they have a higher propensity to leave if wages are cut, but also because a lower fraction of their remuneration is due to bonuses and premia. In line with this argument, we find that DRWR is smaller for categories of workers characterised by lower earnings and fewer bonus payments.

Differences in DRWR across sectors are also substantial. It varies from 0.35 in the transport and storage sector to 0.80 in construction. Regressing our measure of DRWR on workforce composition, sector characteristics and a decentralised wage bargaining index (measured by the percentage of workers that are subject to a firm-level collective wage agreement), we find that DRWR is higher in sectors with (i) a larger proportion of white-collar workers, (ii) larger firms, (iii) more labour-intensive production technology, (iv) stronger competition on the product market, and (v) more centralised wage bargaining.

In order to properly understand this last finding, it should be noted that sector-level collective wage agreements play a dominant role in wage-setting practices in Belgium. There are very widespread, their coverage is very high and they provide a lower bound for wages by occupation, sector, and sometimes age or tenure. In this context, our finding of lower wage rigidity in sectors where firm-level agreements are more common points to the role of firm-level bargaining in accounting for firm-specific economic conditions, something which may ease wage moderation in adverse times.

1. Introduction

Over the last few decades, substantial effort has been devoted to measuring wage rigidity and understanding its macroeconomic implications. Macroeconomic theories have singled it out as a source of resistance to wage moderation and therefore as a cause of high and persistent unemployment (see e.g. Jackman et al., 1991). Moreover, it was suggested that rigid wages can be a cause of less frequent changes in prices of products with a high labour share (see Altissimo et al., 2006, Alvarez et al., 2006, Dhyne et al., 2006, Vermeulen et al., 2007). In turn, price stickiness leads to higher output volatility in response to shocks, which requires larger interest rate changes to affect inflation (see e.g. Altissimo et al., 2006). For example, the New-Keynesian model of Blanchard and Gali (2007) shows that, under real wage rigidity and price rigidity, the optimal monetary policy is no longer focused on inflation targeting, and should instead aim to reduce, although not eliminate altogether, the volatility of both inflation and unemployment.

Although many papers provide estimates of wage rigidity, few examine the factors underlying wage rigidity. For this aim, a comparison between the extent of wage rigidity across well-defined samples, such as countries, individuals, or sectors, is needed. This paper investigates the sources of wage rigidity using a large matched employer-employee dataset of individual earnings backed up with additional firm-level and sector-level data. Labour market rigidities can differ substantially between groups of workers and between sectors of economic activity. Analysing differences across sectors is a natural approach to finding relevant factors of wage rigidity. In particular, it provides the appropriate aggregation level for product market competition and institutional arrangements on wage bargaining. In Belgium, wage bargaining takes place primarily at the sector level. The outcomes of these collective agreements have a strong influence on individual wages and wage changes. However, at the individual firm level, wages may be set above the sector minima, creating a wage cushion that enhances flexibility.

It is worth looking at the main findings of some previous studies, irrespective of the measure of wage rigidity/flexibility adopted. For example, cross-country analyses have highlighted the role of labour market institutions, such as unionisation, centralisation, coordination and coverage of wage bargaining. Using a cross-country analysis, Dickens et al. (2006) point to national labour market institutions as factors explaining differences in the level of downward wage rigidity measured at the microeconomic level. More specifically, they show that unionisation and collective bargaining coverage at the country level are positively related to wage rigidity. Clar et al. (2007) perform a meta-analysis indicating that union density, centralisation of wage bargaining and employment protection legislation are negatively related to real wage flexibility in OECD countries. On the contrary, coordination of wage bargaining, which allows for internalisation of the effects of wage changes on the economy, makes wages more responsive to labour market conditions and therefore increases real wage flexibility. Using industry-level data from OECD countries, Holden and Wulfsberg (2008) find that downward nominal wage rigidity is higher in countries where employment protection legislation is stricter, union density is higher and unemployment is lower.

Differences in wage rigidity according to worker types were pointed out by Campbell (1997). He finds that wage flexibility, defined as the responsiveness of occupational wages to aggregate unemployment, is higher for blue-collar workers than for white-collar workers. Du Caju et al. (2007) provide estimates of downward wage rigidity using the same data and methodology as in this paper. They highlight differences across occupation, age, wage level, etc. but provide no formal statistical tests of these differences.

The literature on wage rigidity involving a sectoral dimension is rather limited. Asking professional wage-setters about the reasons for wage rigidity, Agell and Bennmarker (2007) find that the effects of firms' profits on wages are important in manufacturing and skilled service sectors, and less important in unskilled services and in the public sector. They interpret this as an indication of incumbent workers' bargaining power and therefore as a possible source of rigidity. Campbell (1989, 1991) provides measures of wage flexibility for the United States, Canada and France based on the response of sector-level wages to the aggregate unemployment rate and to sector-specific product demand. Among others, he finds that sectors with a larger percentage of blue-collar workers are characterised by a higher degree of wage flexibility. His results for the United States also indicate that wage flexibility is lower in more capital-intensive sectors. Finally, he finds no robust evidence that unionisation reduces wage flexibility.

In sum, the existing literature identifies several variables driving wage rigidity, such as those related to workers (e.g. occupation), the firm's characteristics (size, sector), production technology (capital intensity), or labour market institutions (for example, unionisation and wage bargaining). However, none of the studies mentioned above provides statistical tests of differences between the categories after controlling for the impact of labour force composition. The composition effects might be especially relevant at the sector level, as some sectors demand very specific labour with respect to skills. For instance, the construction sector employs a disproportionate number of blue-collar workers. The aim of this paper is to determine the relevant factors explaining differences in wage rigidity across sectors. We evaluate the importance of labour force composition, sector-specific characteristics such as firm size, capital intensity and competition, and sector-specific institutional features related to wage bargaining.We rely on a large microeconomic dataset on individual earnings from administrative sources for Belgium over the period 1990-2002. Du Caju et al. (2007) use the same dataset and show that there is virtually no downward nominal rigidity (DNWR) during this period in Belgium, a country with full automatic indexation of wages. For this reason, we focus on downward real wage rigidity (DRWR) which we estimate using the procedure described in Dickens and Goette (2006).

On the empirical side, alternative measures of wage rigidity have been proposed. There is extensive literature measuring wage rigidity with macroeconomic data. Using aggregate data, wage flexibility is usually defined as the responsiveness of wages to economic fluctuations, often proxied by the unemployment rate (see, for instance, Layard et al., 1991, or the papers considered in Clar et al., 2007). In addition, there is a growing volume of studies using microeconomic data. Some of these are based on the response of individual wages to economic conditions (e.g. Altonji and Devereux, 1999). Some others construct measures of wage rigidity from the evidence of small wage cuts and concentration of wage changes around some natural reference point such as zero or the inflation rate (see Kahn, 1997, Card and Hyslop, 1997, or more recently, Dickens et al., 2006, 2007).

Using a large microeconomic dataset provides enough freedom to evaluate DRWR for narrowly-defined samples. For example, we are able to estimate DRWR for young blue-collar workers in a given industry in a particular year. By doing so, we can better examine differences across workers and assess potential effects of workforce composition on sector-level DRWR. Although measures of wage flexibility can be obtained by regressing sector-level wage data (as in Campbell, 1989, 1991) on aggregate unemployment and sector-level growth, it is more difficult to derive such measures for occupational groups since there is no natural proxy for economic conditions. Using a measure of wage rigidity based on individual wage data allows us to examine in a consistent way differences across workers and differences across sectors. One characteristic of our measurement compared to aggregate methods is that we focus on wage changes of workers in a continuing employment relationship. Results from Fehr and Goette (2005) for Switzerland and Haefke et al. (2008) for the United States indicate that aggregate wage flexibility may be larger thanks to a stronger response of entrant wages to economic fluctuations. However, in Belgium the existence of pay scales may limit the scope for differentiated pay policy.[1]

The paper is organised as follows. Section 2 describes the dataset, relevant institutional features of the Belgian labour market and sector-specific characteristics, as well as the methodology. Results are reported in Section 3. First, we provide some estimates of DRWR. These highlight substantial differences across workers and sectors. Second, we examine differences across worker types and shed light on the importance of labour force composition effects. Next, we investigate additional factors explaining differences in downward real wage rigidity between sectors. Section 4 concludes. Appendix A defines the variables used in the paper, while Appendix B provides robustness tests with respect to outliers and alternative definitions of variables.

2. Institutional background, data, and methodology

2.1 Institutional background

Some important institutional features of the labour market affect individual wages in Belgium, such as indexation and sector-level collective bargaining agreements, which can possibly be supplemented with agreements concluded at the firm level. These features explain why Belgium is characterised as a country with high real wage rigidity (see Dickens et al., 2006, or Du Caju et al., 2007). We briefly describe these characteristics of the Belgian labour market. Firstly, as in several countries, a minimum wage is legally binding. Also, practically all employees' gross wages are linked to a consumer price index through an automatic indexation mechanism.[2] This effectively

[1] Preliminary results indicate no significant difference in DRWR across sectors with different quit or labour turnover rates.

limits the scope for real wage cuts and explains why Belgium has been characterised as a country with high downward real wage rigidity and low nominal wage rigidity.

Secondly, as in many other countries, wages in Belgium are largely determined at the sector level. The level of gross wages is mainly determined through agreements concluded in joint committees set up for each sector of economic activity.[3] In many sectors, pay scales are set for blue-collar and white-collar workers separately. This may contribute to observed differences in wage dynamics for blue- and white-collar workers. Indeed, in the joint committees for blue-collar workers, pay scales are primarily fixed in relation to the job description. Variations depending on age or length of service are not common. For white-collar workers, the pay scale usually varies not only according to category, but also depending on age or tenure.[4] The joint committees at the sector level are also the main bargaining unit for the negotiations on collective wage increases. Quite often, these collective wage increases are defined as a rise in absolute terms of the (sometimes only minimum) pay scales, meaning that employees with wages above the scale can obtain a lower percentage collective wage increase. For the period under review, a lot of employees receive automatic wage increases, negotiated in sector-level collective agreements. These depend on age and, to a lesser extent, tenure.

In addition, firm-level agreements can complement sector-specific agreements. According to the favourability principle in hierarchical wage bargaining, the negotiated wages in these firm-level agreements cannot be below the sectoral agreements.[5] Decentralised wage setting through single-employer (SE) wage agreements is very common in the chemicals and transport equipment industries, and very rare in the construction and business services sectors. Also firm-level agreements are more common in large firms with stronger union representation than in smaller firms. Note that union representation is compulsory in firms with 50 employees or more. SE collective wage agreements make it possible to take firm-specific features more closely into account in the wage-setting process. In Belgium, companies that do not have a firm-level agreement tend to stick to the sector agreement. Firms with an SE agreement generally pay more and have a more dispersed earnings structure. This provides them with a wage cushion above the sector minima, creating some margin of manoeuvre for wage adjustments. Individual data from the Belgian Structure of Earnings Survey (SES) show that firms with SE agreements for blue-collar and white-collar workers pay 12% higher earnings and bonuses are 53% higher. Furthermore, the

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2 Specifically, the index considered is the consumer price index excluding alcoholic beverages, tobacco and motor fuels. In some segments of the labour market, wages are indexed at fixed points in time (e.g. every one to twelve months), while in others, wages are index-linked each time the index exceeds a certain threshold (the threshold value is defined as the previous value plus two percent).

3 They are called joint committees ('commissions paritaires'), because employers and employees share an equal representation in them. As the notion of economic sector is sometimes very narrowly defined, the number of joint committees exceeds 100. The outcome of these sector-specific negotiations cannot undercut the legally determined guaranteed minimum wage. The actual minimum pay by sector, occupation and sometimes age or tenure, defined within joint committees, exceeds the legally guaranteed minimum. There are some exceptions for workers less than 21 years old.

4 During the period under review, age-related pay scales were not against European anti-discrimination rules and were applicable to the majority of Belgian white-collar workers.

5 Opt-out clauses are possible but are very rare.

standard deviation of earnings is 2% larger, and that of bonuses is 16% larger in firms with SE agreements compared to firms with no SE agreements. In view of these gaps, one may expect to find less DRWR in sectors where SE agreements are more common, as is the case when firms are larger.

2.2 Data

To measure downward real wage rigidity, we rely on an administrative employer-employee database on individual labour earnings for Belgium, collected by the social security system. The data contain information on annual gross earnings (including bonuses and compensation for overtime hours), annual working days, age, sex and occupation category (blue-collar or white-collar). The dataset contains a sample of around one-third of workers in the private sector and covers the period 1990-2002. It includes all persons that were born between the 5^{th} and the 15^{th} day of any month, except those employed by firms with less than 5 employees or by independent workers. The dataset covers all sectors of activity including services. We focus on in firms active in branches with NACE codes from D to K, i.e. we exclude agriculture, extraction industries and non-commercial services.

We restrict the sample to workers above the legal minimum age of compulsory schooling and below the retirement age, i.e. men between 18 and 64 and women between 18 and 59. We also exclude earnings below the legal minimum wage and we drop the same number of observations from the upper tail of the distribution. In this way, we attempt to exclude outliers and possibly extreme variations in individual annual earnings. Finally, we restrict the sample to full-time permanent job stayers. Since the dataset does not report the type of contract (fixed-term or indeterminate length), we define these permanent job stayers as working at least 11 months for the same employer over two consecutive years. In this way, we allow permanent workers to have at most one month of sick leave (or other "abnormal" days off) per year, in order to distinguish them from temporary workers. We refer to Du Caju et al. (2007) for more details on the data.

It is important to note that annual earnings include variable compensation components, such as bonuses, premia, and overtime hours. Not all of these are subject to automatic increases such as indexation and collectively bargained increases. Therefore, annual earnings may be more flexible than the base wage. Further, because the importance of extra wage components varies across workers, firms and sectors, these may explain differences of wage rigidity across sectors. For example, bonuses and premia may be higher for white-collar workers, older and higher-earnings employees, while compensation for overtime hours may be more common for blue-collar workers.

The individual earnings data are complemented with information from firms' balance sheets.[6] Also, we use individual data from the Belgian Structure of Earnings Survey (SES), for the 1999, 2000, 2001 and 2002 waves.

Individual annual earnings data are used to estimate downward real wage rigidity by occupation, age category and sector. These rigidity measures are then related to three types of variables, namely worker characteristics, sector characteristics and decentralisation of wage bargaining. The first set consists of variables related to worker type. This is the case of the occupation dummy that equals unity for blue-collar workers, and of age dummies that identify workers aged between 18 and 24 years, those between 25 and 44 years old, and those older than 45.[7] We also consider the median level of earnings, computed from the individual earnings dataset, and the median level of bonuses, as reported in the four SES waves between 1999 and 2002. Note that this variable includes compensation for overtime hours.

The second set of variables describes sectoral characteristics. From firms' balance sheets, we define the median firm size as the median within the sector of the number of employees, and the capital-labour ratio as the median within the sector of firm-specific capital-labour ratios. Moreover, we estimate a measure of competition recently proposed by Boone et al. (2007), i.e. the elasticity of a firm's profits with respect to its marginal costs (profit elasticity). The intuition behind profit elasticity is that firms in less competitive sectors are not pure price takers, hence a given percentage increase in costs can be accommodated by a price rise, in turn leading to a smaller fall in profits. The profit elasticity is thus larger for more competitive firms. Using firm-level data for each branch, we regress log profits on log variable costs (for more details on theoretical derivation as well as its relation to other measures of competition, see Appendix A). As a robustness test, we also consider two alternative measures of competition: the Herfindahl index which measures concentration within the sector, and sector-specific estimates of the price cost margin given by Christopoulou and Vermeulen (2007). As argued in Boone et al. (2007), the three measures would correctly capture strengthened competition resulting from a fall in entry costs and a consequent increase in the number of firms. However, the Herfindahl index fails to capture any increase in competition that might cause inefficient firms to close down, because in such a case, concentration in the industry increases. It would nevertheless be misleading to interpret this as a fall in competition. Further, these authors argue that empirical measures of the price-cost margin, such as the ratio of profits to sales, may be less suited in highly concentrated markets. The estimates of Christopoulou and Vermeulen (2007) rely on the estimation of structural equation, but they are time-invariant. Because the profit elasticity overcomes the drawback of the other measures and is time-varying, it is our preferred measure of competition.

Finally, the third type of variable refers to sectoral wage bargaining practices, i.e. the coverage by collective wage agreements at the sector or firm level. For Europe in general and Belgium in particular, this provides a much better indicator of union bargaining power than union membership, for example. The reason is that, unlike in the US, wage agreements are negotiated between employers' representatives and workers' representatives, but apply to all workers, regardless of whether they are unionised or not. As explained above, sector-level multi-employer agreements apply generally in Belgium. As an indicator of decentralised wage setting, we calculate the average

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[7] The thresholds are defined so as to have enough observations of individual earnings changes in each category to estimate DRWR.

proportion over time (1999-2002) of workers covered by a single-employer (SE) wage agreement, from the SES dataset. Such agreements are expected to provide the firm with more flexibility as compared to the multi-employer (ME) agreements. Moreover, firms applying SE agreements are more likely to negotiate individually wage conditions that are more favourable than those of the collective agreement for part of their workforce, as indicated by a larger wage dispersion in firms that have their own wage agreement. Appendix A gives more information on data sources and definitions.

Table 1 provides information on sectoral differences in the variables of interest. For example, the proportion of blue-collar workers is very large in the construction and other manufacturing sectors, and very low in financial and business services. Earnings and bonuses are particularly high in the chemical industry and in financial services. At the other extreme, earnings and bonuses are the lowest in the construction, and hotels and restaurants sectors. Turning to production characteristics, chemicals, non-metal manufacturing, transport storage and business services are capital-intensive sectors, while construction is the most labourintensive industry. Firms are larger in chemicals, textiles and transport equipment industries, and smaller in services.

Table 1 - Labour force composition, wages and sector characteristics - averages over time

Sector	Pct of white-collars	Average Age	Median earnings[a]	Average bonus[b]	Median firm size[c]	Median K/L[d]	Profit elasticity[e]	SE coverage of blue-collars[f]
food	41.66	36.15	72.41	2671	6	17.8	7.957	35.50
textile	33.62	36.75	58.35	968	11	11.1	9.514	11.34
wood and paper	43.54	36.84	79.10	2326	4	18.5	7.436	27.51
chemicals	60.27	37.87	101.34	4122	13	20.7	7.809	54.80
non metal	34.39	38.86	78.24	2292	7	20.5	8.514	37.49
metal	35.08	38.44	81.63	2509	7	13.8	8.119	38.65
machinery and equip.	47.51	37.46	81.11	2930	7	10.6	8.642	30.54
transport equipment	28.27	37.55	89.84	2428	11	11.4	9.877	42.89
other manufacturing	22.93	36.81	60.73	1327	5	12.3	9.159	14.44
construction	21.29	36.77	68.86	875	4	10.0	8.432	2.38
trade	72.58	36.20	71.02	3073	3	14.5	9.821	15.10
hotels and restaurants	36.87	34.12	53.67	354	3	11.8	8.189	10.15
transport and storage	46.14	37.41	74.29	1772	5	22.4	5.784	20.58
financial services	97.79	38.44	104.34	6043	2	16.2	5.473	34.02
business services	83.13	35.13	83.64	3354	2	19.5	6.007	3.61
Mean	47.01	36.99	77.24	2469	6.0	15.4	8.049	25.27
Standard deviation	22.25	1.26	14.34	1415	3.4	4.20	1.388	15.54

Notes: [a] Gross total daily earnings in euro.
[b] Annual bonuses in euro.
: [c] Number of employees.
[d] Median capital-labour ratio measured in thousands of euro.
[e] Values calculated for each branch and year. The table reports median over years.
[f] Percentage of blue-collar workers employed in firms with single-employer agreement.

According to the profit elasticity, competition is fiercer in other manufacturing, transport equipment and trade and low in business, financial services and in transport and storage. Note that alternative indicators of competition are not always consistent with the profit elasticity. We therefore evaluate the robustness of our results with respect to the choice of competition indicator in the appendix. Finally, it should be noted that decentralised bargaining through SE agreements is much more widespread in the chemical industry and is essentially absent in the construction and business services, i.e. in sectors with centralised bargaining.

2.3 Methodology

This paper investigates the determinants of the differences in DRWR across workers and sectors. We focus on DRWR because previous results characterise Belgium as a country with one of the highest levels of DRWR and one of the lowest levels of DNWR (Dickens et al., 2007, Du Caju et al., 2007), consistent with the system of automatic wage indexation. For this purpose, we proceed in two steps. First, we estimate DRWR year by year for each group, defined either by occupation, age and sector, or simply by sector of economic activity. Second, we regress our measure of DRWR on a set of potential explanatory variables.

2.3.1 Measuring downward real wage rigidity

Our measure of DRWR is based on the methodology described in Dickens and Goette (2006).[8] This measure attempts to capture the fraction of workers who would not receive a real wage cut when they were due for one, no matter what the reason for the wage cut. Briefly, the method is based on the comparison of the observed distribution of individual nominal wage changes with the notional distribution, i.e. the one that would prevail under perfect wage flexibility. The latter is assumed to be symmetric. On the contrary, downward wage rigidity typically generates asymmetry and spikes around the reference point. The reference point for real wage rigidity is expected inflation, and that for nominal wage rigidity is zero. Indeed, wage changes that would have fallen below the reference point under perfect flexibility will appear at or above the reference point in the observed distribution. Therefore, the observed distribution of individual wage changes will be characterised by fewer observations below the median than above it, i.e. it will be asymmetric. Moreover, wage changes that would have been below the reference point under perfect flexibility may be concentrated at the reference point, generating a spike in the observed distribution of wage changes. As an illustration, figure 1 below shows the histogram of earnings changes for textiles in 2002. The asymmetry of the distribution is quite clear, as is the spike around the collective wage increase level.

8 We make the following choice of the parameters., We allow the mean of π^e to be unrestricted in the 0-4 percent band and its variance to range from 4E-06 to 3.6E-05. See Du Caju et al. (2007) for a discussion on specification issues. In Du Caju et al. (2007) we provide a more detailed description of the procedure and a comparison with other methodologies.

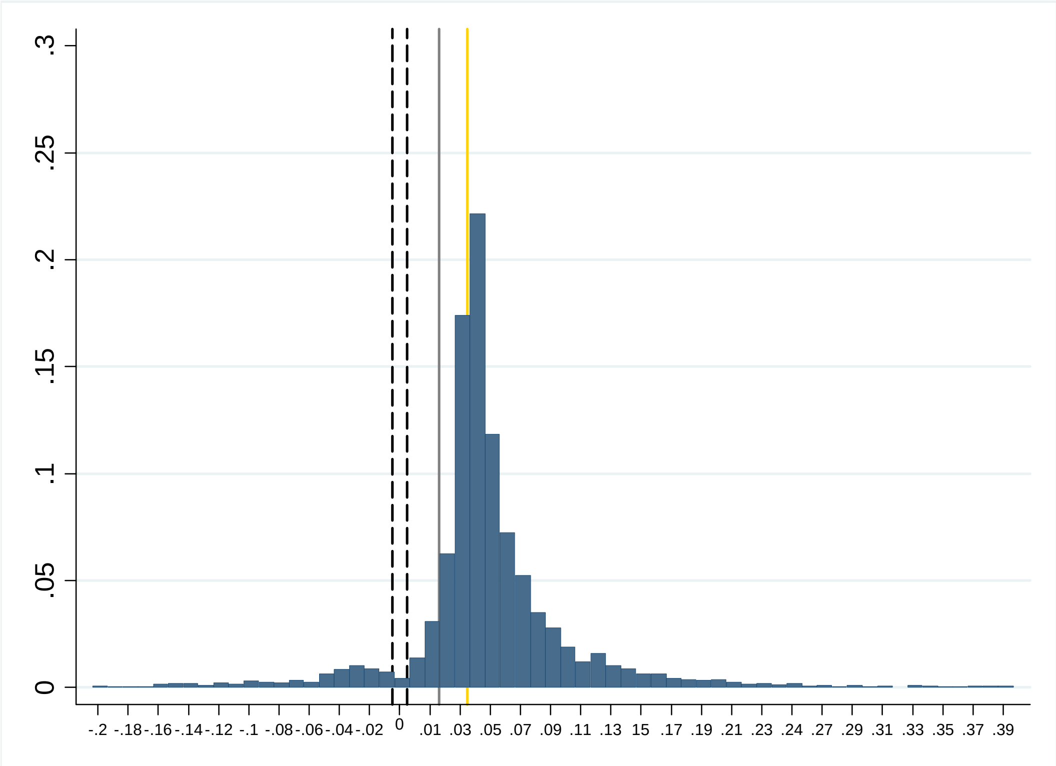

Figure 1 - Distribution of earnings changes for the textile industry in year 2002

Note: grey solid line shows the economy-wide CPI inflation while the yellow line is the economy-wide total collective wage increase.

Dickens and Goette (2006) propose a Mixed Method of Moments estimator to evaluate the extent of DNWR, the level of DRWR as well as the reference point for real wage rigidity. This method has been applied within the International Wage Flexibility Project (Dickens et al., 2007), and more recently in the Wage Dynamics Network for Belgium (Du Caju et al., 2007), Messina et al., 2008). The method offers several advantages. First, the reference point for real wage rigidity, i.e. expected inflation, is directly estimated from the data rather than provided by the econometrician based on outside estimates. Second, the method takes into account measurement errors in the wage changes variable. Third, it requires only information on wage changes. However, because it is based on the estimated distribution of wage changes, it demands datasets with a large cross-section dimension. Among its drawbacks is the fact that identifying DRWR and DNWR becomes an issue in years with very low inflation, where the reference point for DRWR comes very close to zero, i.e. the reference point for DNWR.

Another strand of the literature proposes alternative measures of downward wage rigidity based on the idea that it implies a smaller response of wages to adverse shocks than to positive outcomes (see, for example, Altonji and Devereux, 1999, or Biscourp et al., 2005). The concept is appealing because it takes into account the motives to cut wages, but it is very demanding in terms of data as it requires information on relevant workers' and firms' characteristics.

Note that, on the one hand, the resistance to wage cuts following negative events implies that the distribution of wage changes is asymmetric should any negative shocks occur. On the other hand, if one observes asymmetry in the distribution of wage changes, one should *a fortiori* find that wages do not respond to negative signals. Therefore the two approaches should lead to identical conclusions about the presence of downward of wage rigidity. A more important difference arises with respect to estimates of the sensitivity of wages to shocks at a more aggregated level. Consider, for example, an adverse shock. Firms may reduce their average wage bill by changing the composition of their workforce, *even if* the wages of job stayers do not fall. In this case, the distribution of individual earnings changes will exhibit no wage cuts, while the estimation of aggregate wage sensitivity will suggest that the average wage has fallen.

2.3.2 Explaining differences in DRWR across sectors

In order to test formally for differences across worker types and the importance of workforce composition in explaining differences in DRWR across sectors, we proceed in two steps. First, we estimate DRWR using the IWFP procedure described in the previous subsection. Second, the estimates of DRWR serve as dependent variables in regression equations with explanatory factors entering as independent variables. We disregard DNWR because our previous findings have shown it to be of little of importance for Belgium (Du Caju et al., 2007).

The dataset enables 90 categories to be considered for each year, defined as the combination of 15 branches, 2 occupation categories and 3 age groups. We consider two occupational categories (blue-collar and white-collar workers) and three age groups (18-24 years, 25-44 years, and 45 years or more). Branches have been defined as follows: (1) food (food products, beverages and tobacco), (2) textile (textiles, textile products, leather and footwear), (3) wood and paper (wood and products of wood and cork, and pulp, paper, paper products, printing and publishing), (4) chemicals (chemical, rubber, plastics and fuel products), (5) non-metal (other non-metallic mineral products), (6) metal (basic metals and fabricated metal products), (7) machinery and equipment, (8) transport equipment, (9) other manufacturing (manufacturing n.e.c., recycling), (10) construction, (11) trade (wholesale and retail trade, repair), (12) hotels and restaurants, (13) transport and storage, (14) financial services (financial intermediation), (15) business services (real estate, renting and business activities). In order to keep enough observations in each category to estimate DRWR, we exclude categories with less than 2,000 observations of earnings changes. Also, we do not consider energy (electricity, gas and water supply) and transport and communication (post and telecommunications) because either the estimates of DRWR are not reliable or the observations appear to be outliers in the regressions estimated below. We also rule out estimates of DRWR that hit the boundary of zero or one as being unreliable (142 cases).

We perform two types of analysis. First of all, we test for significant differences in DRWR across workers. Secondly, we examine factors that explain differences in DRWR across sectors. In the first case, we estimate DRWR for each year, occupational group, age group and sector. Formally, we denote the estimates of downward real wage rigidity as $DRWR_{kajt}$, where *k* stands for occupation category (blue-collar or white-collar), *a* for age categories, while the sector is represented by the subscript *j* and the year by *t*. The regression equations that we estimate take the following form:

$$DRWR_{kajt} = \alpha_t + \beta_1 \text{ D white-collar}_{kajt} + \beta_2 \text{ D age:25-44}_{kajt} + \beta_3 \text{ D age:45+}_{kajt} + \beta_4 X_{kajt} + \varepsilon_{kajt}, \quad (1)$$

where α_t is a time-varying constant, D indicates that the variable is a dummy and X_{kajt} stands for a continuous explanatory variable, like earnings or bonuses.

In the second case, in order to analyse the impact of workforce composition, technology, competition and bargaining institutions on differences in DRWR across sectors, we follow the same idea as above, except that we now only estimate DRWR across 15 sectors and over several years. In the following regression, our explanatory variables are defined only over sectors and years. We control for workforce composition by adding the average age of workers and the percentage of blue-collar workers, both defined by sector and year. We consider the effect of each explanatory variable on its own after controlling for workforce composition. In a later stage, we combine the explanatory variables into a single model along the following lines:

$$\begin{aligned} DRWR_{jt} = {} & \alpha_t + \beta_1 \text{ age}_{jt} + \beta_2 \text{ blue-collar}_{jt} + \beta_3 \text{ size}_{jt} + \beta_4 \text{ K/L}_j + \beta_5 \text{ profit elasticity}_{jt} + \\ & + \beta_6 \text{ SE coverage}_{jt} + \varepsilon_{jt}, \end{aligned} \quad (2)$$

where K/L is the capital-labour ratio, profit elasticity is our preferred measure of competition and SE coverage stands for the percentage of blue-collar workers covered by single-employer collective agreements.

Estimates of equations (1) and (2) by OLS may nevertheless be plagued by several econometric problems. First, in Section 3.3 we take into account potential endogeneity of the profit elasticity, and consider estimation with instrumental variables to correct for the simultaneity bias. Second, our dependent variable can only take on values between 0 and 1, while under the standard assumption of an OLS model with fixed explanatory variables and normally distributed error term, the dependent variable should be also normally distributed. Models for dependent variables that vary on the [0.1] interval were developed by Papke and Wooldridge (1996) who propose a generalised linear regression model and use quasi-maximum likelihood method (QML) for its estimation. In Appendix B2, we re-estimate all the models presented in the paper and conclude that the point estimates of coefficients estimated by QML and OLS are very similar. This is not surprising in the light of the results that we obtained from specification error tests of the OLS model. Using Ramsey's (1969) regression error specification error test (RESET), we conclude in all cases that the OLS models do not suffer from specification error (see Appendix B2 for more details). Third, our estimated standard errors may be downwards biased because some variables are estimated or proxied rather than truly observed. For instance, the profit elasticity is a generated regressor. Lastly, some explanatory variables are time-invariant, such as the capital to labour ratio and the decentralisation of wage bargaining.[9] However, given the small number of time periods (12) and sectors (15), our view is that using sophisticated econometric corrections (such as bootstrap methods or clustered robust standard errors) is beyond the scope of what can be learned from our data. It should be noted that the above-mentioned issues do not affect the point estimates of the coefficients.

3. Results

In Section 3.1, we introduce the values of DRWR that were estimated by the IWFP procedure and compare the average levels across age and occupation categories and across sectors. We discuss possible explanations for the differences and compare the results with other findings in the literature. Section 3.2 tests the importance of workforce composition effects for DRWR in a model varying over sectors, age and occupation categories and time. At the same time, we consider the effect of earnings level and bonuses on DRWR. Section 3.3 focuses solely on differences across sectors and analyses DRWR varying only across sectors and years. We investigate the role of firm size, capital to labour ratio, profit elasticity and decentralisation of wage bargaining. We examine the effect of each explanatory variable on its own after controlling for workforce composition. Finally, the explanatory variables are combined into a single model which is then used to decompose the contribution of each variable to sector-specific DRWR. Robustness tests with respect to the estimation issues discussed in the preceding section are reported in Appendix B.

3.1 Estimates of downward real wage rigidity

Table 2 presents the average values of DRWR for the sectors and worker categories considered in this paper. The average DRWR across sectors, equal to 0.58, is in line with our previous findings (see Du Caju et al., 2007) and points towards strong downward real wage rigidity in Belgium. Such a high value ranks Belgium as the country with the highest DRWR among the 16 countries participating in the Inflation Wage Flexibility Project (cf. Figure 4 in Dickens et al., 2006).

Table 2 documents that white-collar workers have more rigid earnings than blue-collar workers. The numbers reported in Table 2 imply that the estimated fraction of white-collar workers subject to DRWR is 10 percentage points higher than that of blue-collar workers. The same conclusion was reported by Campbell (1997) for the US, based on the observation that wages of white-collar workers are much less responsive to the aggregate unemployment rate than blue-collar workers' wages. This result is consistent with the shirking model of Shapiro and Stiglitz (1984) and with the turnover model of Stiglitz (1974). These models are based on the idea that firms may be less inclined to cut wages of white-collar workers because they are more difficult (costly) to replace and

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[9] Indeed, robustness tests (not reported for the sake of brevity) that take into account intra-class correlation, indicate that robust standard errors are larger than the OLS estimates. This results from the fact that under intra-class correlation, each observation contains less unique information and the effective sample size is reduced.

to monitor, and therefore are more likely to shirk their jobs. Franz and Pfeiffer (2006) report survey evidence for Germany indicating that the main reasons for wage rigidity of high-skilled workers are the existence of specific skills and the negative signal a wage cut may represent for newly-hired staff. On the contrary, wage rigidity of less-skilled workers is mainly attributable to labour union contracts and implicit contracts. In Belgium, in addition, white-collar workers obtain automatic wage increases with age or tenure, while this is rarely the case for blue-collar workers. This makes white-collar workers less likely to experience real wage cuts.

Table 2 - Estimates of DRWR

Category	average DRWR	st. dev.
Blue-collar workers	0.580	0.261
White-collar workers	0.641	0.213
Workers aged 18-24 years	0.630	0.217
Workers aged 25-44 years	0.593	0.230
Workers older than 44 years	0.612	0.265
food	0.526	0.126
textile	0.600	0.178
wood and paper	0.648	0.108
chemicals	0.467	0.173
non-metal	0.483	0.101
metal	0.553	0.142
machinery and equip.	0.618	0.081
transport equipment	0.517	0.115
other manufacturing	0.681	0.277
construction	0.801	0.239
trade	0.648	0.188
hotels and restaurants	0.590	0.214
transport and storage	0.354	0.145
financial services	0.627	0.195
business services	0.668	0.114
Entire sample (av. over sectors)	0.581	0.193

Notes: DRWR estimated by the IWFP procedure, see Section 2. Results for sectors are averaged over years and the entire sample is the average over sectors and years. Results for occupational categories and age categories were obtained as averages from estimates of DRWR varying across occupation, age, sectors and years.

Young workers (aged between 18 and 24 years) have more rigid earnings than older workers, consistent with previous findings in Du Caju et al. (2007). The result may be explained by the shirking model and the adverse selection model of Weiss (1980) applied to job quits. It predicts that younger workers are more likely to quit when their earnings increases are below their expected bargaining reference point because the cost of job loss is smaller for them than for older workers, i.e. finding a job is more difficult for older workers and, in addition, they might lose their tenure-related component of compensation. Furthermore, automatic tenure and age-related wage increases are more prominent for younger workers, while extra wage components are smaller, leading to less flexible earnings.

The estimates of DRWR across sectors highlight substantial variation; DRWR ranges from 0.35 to 0.80. The highest DRWR is observed in the following sectors: construction, business services, trade, and wood and paper. Sectors with the lowest degree of DRWR are transport and storage and chemicals. Below, we consider a range of factors that can explain these differences in DRWR across workers and sectors.

3.2 Workforce characteristics and composition effects

In Table 2, we first test formally whether there are differences in DRWR across workers, then consider the impact of payroll policies on the level of DRWR. More specifically, we regress our measure of DRWR estimated for each year, occupation, age group and sector, on dummies for occupation and age category. We then expand the equation with the median earnings and median bonus per category. Table 2 presents the results estimated by least squares, Appendix B shows that the results are robust to accounting for a dependent variable bounded between zero and one.

Table 3 - OLS estimates of eq. (1), DRWR per year, occupation, age category and sector

Dep. v. $DRWR_{kajt}$	Model (1)	Model (2)	Model (3)	Model (4)
D white-$collar_{kajt}$	0.070***	0.084***	0.133***	0.109***
	(4.05)	(5.11)	(5.12)	(4.98)
D $age{:}25\text{-}44_{kajt}$	-0.051**	-0.059***	-0.021	-0.022
	(-2.29)	(-2.74)	(-0.89)	(-0.91)
D $age{:}45+_{kajt}$	-0.032	-0.047**	0.006	0.018
	(-1.44)	(-2.20)	(0.25)	(0.62)
$bonus_{kaj}^{\dagger}$			-0.030***	
			(-3.23)	
$earnings_{kajt}^{\dagger}$				-1.790***
				(-2.88)
Constant	0.488***	0.479***	0.493***	0.562***
	(13.88)	(10.98)	(14.11)	(12.94)
Year dummies	yes	yes	yes	yes
Sector dummies	no	yes	no	no
R^2_{adj}	0.056	0.199	0.068	0.065
Number of obs.	758	758	758	758
F test for sector dummies [p-value]		11.30 [0.000]		

Notes: † measured in thousands of euro.
*/**/*** indicate significance at the 0.10, 0.05 and 0.01 level, respectively.
t-statistics in brackets.

Model (1) shows that the earnings of white-collar workers are significantly more rigid than those of blue-collar workers. DRWR is highest for workers aged between 18 and 24 years, however, the difference between the youngest and oldest worker category is not statistically significant. One particular reason is that coefficients in Model (1) reflect both the variation in DRWR across sectors and within sectors. In Model (2) we add sector dummies, thus effectively removing the variation across sectors, and conclude that workers between 18 and 24 years have a significantly higher degree of rigidity than the remaining two categories when only the variation within sectors is considered. The increase in the coefficient of determination from 0.06 in Model (1) to 0.20 in Model (2) suggests that sector-specific factors contribute to explaining DRWR beyond the effects of occupation and age. By running an F-test for equality of the sector dummies in Model (2), we conclude that the differences across sectors are statistically significant.

As discussed in Section 2.1, one of the reasons why younger workers may have more rigid wages is that the fraction of labour compensation due to flexible components such as bonuses and premia is typically smaller for younger people. Because these can be easily cut, earnings should be less rigid the larger the bonuses. Indeed, models (3) and (4) show that DRWR is lower for worker categories and sectors with a higher bonuses and earnings.[10] Further, when bonuses are included in equation (1), age dummies are no longer significant. In the same vein, DRWR is lower for higher-earning categories. Besides the argument related to bonuses and premia, another explanation is that low wages are close to the institutional minimum wage or to sectoral pay scales and therefore cannot be reduced freely. Lastly, wage levels are typically higher and more dispersed in firms with SE wage agreements as opposed to sector-level or multi-employer (ME) agreements.[11] As argued by Cardoso and Portugal (2005), higher and more dispersed wages in firms with SE agreements provide employers with a flexible wage cushion over and above the sectoral minima. This yields more flexibility in wage adjustment. We examine this issue in more detail in the next section.

In sum, we have shown that earnings of white-collar workers and workers between 18 and 24 years are significantly more rigid than those of blue-collar workers and older workers. Further, age-related aspects may explain inter-sectoral differences across workers rather than inter-sectoral differences in DRWR. The results also suggest that sector-specific factors should contribute to explaining DRWR beyond the effects of occupation and age. Finally, as expected, bonuses and higher earnings generally tend to lower downward real wage rigidity.

3.3 Sector-specific factors driving DRWR: technology, competition and institutions

In order to analyse additional factors that drive differences in DRWR across sectors, like technology, competition and wage-bargaining institutions, we consider a dataset that varies only across sectors and over time. We estimate similar equations to those used in the previous section, except that we replace age and occupation dummies by average age and the percentage of blue-collar workers per sector and year to control for workforce composition.

We disregard the earnings level and bonuses because these variables are the outcome of the firm’s compensation policy, as is DRWR, and are therefore potentially endogenous. We prefer to keep variables that are independent of the firm's pay policy, such as competition indicators, capital intensity or SE agreement coverage.

Table 4 reveals that, with the exception of two models, average age and the percentage of blue-collar workers are not statistically significant. Combined with our previous results presented in Table 3, we can conclude that earnings of older workers and blue-collar workers are less rigid, whatever the sector of economic activity. However, differences across sectors in the average age do not explain differences in DRWR across sectors.

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10 These results are robust to considering the average earnings and the average bonus instead of the medians. For space considerations, the results are not reported but are available on request.

11 See also evidence in Card and de la Rica (2006), Cardoso and Portugal (2005), Dell' Aringa and Lucifora (1994), Gerlach and Stephan (2006), Palenzuela and Jimeno (1996) and, for Belgium, Rycx (2003). See also the figures reported in Section 2.1.

Least squares estimates of equation (2) are shown in Tables 4 and 5. Robustness with respect to Papke and Wooldridge's (1996) estimation that takes into account the bounded nature of DRWR (between zero and one) are reported in Appendix B. The size of the coefficients and the significance is similar.

Table 4 - Sector-specific factors affecting DRWR, OLS estimates

Dep. var. $DRWR_{jt}$	(1)	(2)	(3)	(4)	(5)
age_{jt}	-0.021*	-0.006	-0.012	-0.020*	0.016
	(-1.91)	(-0.52)	(-1.11)	(-1.84)	(1.14)
$blue\text{-}collars_{jt}$	-0.000	0.001	-0.002**	-0.001*	-0.000
	(-0.42)	(0.79)	(-2.32)	(-1.71)	(-0.74)
$size_{jt}$		-13.90***			
		(-2.91)			
K/L_j			-0.017***		
			(-4.91)		
Profit $elasticity_{jt}$				0.029**	
				(2.42)	
SE $coverage_j$					-0.005***
					(-4.17)
Constant	1.264***	0.762*	1.252***	1.080***	0.055
	(3.11)	(1.76)	(3.29)	(2.65)	(0.11)
Year dummies	yes	yes	yes	yes	yes
Sector dummies	no	no	no	no	no
R^2_{adj}	0.085	0.126	0.201	0.112	0.171
Number of obs.	173	173	173	173	173

Notes:

age_{jt} is the average age of workers;
$blue\text{-}collars_{jt}$ is the percentage of blue-collar workers;
$size_{jt}$ is the average size of firms, measured in thousands of employees;
K/L_j is the capital-labour ratio, measured in thousands of euro;
Profit $elasticity_{jt}$ is our preferred measure of competition
SE $coverage_j$ is the percentage of blue-collar workers covered by single-employer collective agreements
*/**/*** indicate significance at the 0.10, 0.05 and 0.01 level, respectively.
t-statistics in brackets.

Next, we examine whether the median firm size within the sector affects wage rigidity. There are several reasons why firm size might affect DRWR. Union representation is compulsory in firms with more than 50 employees in Belgium, which may ease the negotiation of wage concessions in adverse times. Also, larger firms typically have more complex compensation structures, offer higher but also more dispersed wages[12], and possibly a larger amount of extra wage components. Also they are more likely to sign SE agreements, which allow for a more flexible wage policy than the sectoral agreements. Earnings decreases in smaller firms are more likely to be bounded by minima collectively agreed outside the firm. On the contrary, in larger firms, the wage cushion (above the sector-level agreement) provides some margin for earnings cuts. Model (2) in Table 4 confirms these arguments. DRWR is significantly lower in sectors with larger firms, all else equal.

12 This is also the case in our sample. For example, the average earnings in firms with less than 25 employees are 30 percent lower than those in firms with more than 500 employees, as is the standard deviation of earnings. More importantly, the mean and standard deviation of earnings changes are 15 percent lower for smaller firms compared to larger firms.

We also study whether production technology and market competition are related to DRWR. First, we introduce the median capital-labour ratio for each sector in Model (3). Our estimates indicate that labour-intensive sectors have higher DRWR. Note that labour-intensive sectors such as construction, textiles and transport equipment, for example, also have a larger proportion of blue-collar workers (see Table 1), whose wages are less rigid. Table 4 shows that capital intensity is negatively related to DRWR after controlling for labour force composition. Our results contrast with the findings of Campbell (1991), who reports a negative correlation between sector-level wage flexibility and the capital-labour ratio in the US. But they are consistent with the finding in Fuss (2008) that wage cuts in adverse times are largely non-existent in the construction sector (the most labour-intensive) contrary to the manufacturing and services sectors. Also, our finding that wage rigidity is stronger in labour-intensive sectors complements the view expressed by the Eurosystem Inflation Persistence Network (IPN) that the higher degree of price stickiness observed in more labour-intensive sectors might result from wage rigidity, see Altissimo et al. (2006), Álvarez et al. (2006), Dhyne et al. (2006) and Vermeulen et al. (2006).[13]

In Model (4), we report results for competition measured through the profit elasticity proposed by Boone et al. (2007) and estimated at the sector level. Controlling for age and occupation, our estimates indicate that sectors with stronger competition experience higher DRWR. One potential explanation is related to wage-bargaining practices. SE wage agreements are more common in sectors where firms are large and have higher market power and where company unions try to appropriate the rents. SE wage agreements are far less common in sectors with small competitive firms. In this case, the main objective of unions is rather egalitarian as they are trying to avoid a wage race to the bottom; they are mainly organised at sectoral level in order to negotiate equal pay within the sector. Note that our finding of a positive relationship between product market competition and DRWR should be treated with some caution. Appendix B provides results based on two additional measures of competition: the Herfindahl index and the price-cost margin. Even though the estimates based on these alternative measures predict the same direction of the impact of competition on DRWR, the coefficients are not statistically significant (see Table B2).

Finally, we examine whether differences in decentralisation of wage bargaining across sectors influence DRWR. In the literature, wage-bargaining institutions have been cited as a cause of differences in downward wage rigidity across countries. Dickens et al. (2006) and Holden and Wulfsberg (2008) relate higher wage rigidity to higher union density and/or bargaining coverage. In the context of our paper, we examine whether sectoral differences in the wage-bargaining mechanism are related to sectoral differences in wage rigidity. As mentioned above, inter-sectoral coordination practices and indexation mechanisms are largely determined at the national level. These are common to all sectors and may explain the high level of DRWR in Belgium compared to other countries. Beyond this, sector-level collective wage bargaining plays a dominant role in wage-

13 Our measure of DRWR is negatively related to the sector-specific frequency of monthly producer price changes in the manufacturing sector, computed as in Cornille and Dossche (2008). This suggests that sectors with higher DRWR also experience higher price rigidity. The correlation coefficient between DRWR and the frequency of producer price change reaches -0.67. We thank M. Dossche for providing us with the estimates of the frequency of producer price change.

setting practices. On top of these, other bargaining characteristics, such as the proportion of firms with SE agreements, vary across sectors. As mentioned above, firm-level or single-employer (SE) agreements lead to higher wages on average, as well as wider wage dispersion across firms because such agreements can better take into account firm-specific characteristics in the determination of wages.[14] In addition, according to Cardoso and Portugal (2005), a higher average wage and wider wage dispersion within firms provide employers with a flexible wage cushion above the sectoral minima, leaving these firms with a wider range of options in their wage-setting policy, i.e. allowing a greater role for workers' and firms' characteristics in remuneration. This, in turn, is expected to reduce downward real wage rigidity. This prediction is confirmed in Model (5) in Table 4. Downward real wage rigidity is lower in sectors with a higher proportion of workers covered by an additional firm-level wage agreement.

In Table 5, we combine the explanatory variables discussed so far into a single model. It has already been suggested that the variables might be collinear which would, in turn, give rise to imprecise estimates of the coefficients in the combined model. For example, larger firms typically offer higher and more dispersed wages. And companies with firm-level agreements are generally larger, and pay higher wages. As before, we omit from the model the earnings level and bonuses.[15] One may argue that these variables are the outcome of the firm's compensation policy, as is DRWR, and are therefore potentially endogenous. We prefer to use variables that are independent of the firm's pay policy, such as competition indicators, capital intensity or SE agreement coverage.

In Model C1 in Table 5, there are two variables that are insignificant at the 10 percent level. One of them is age. Since we concluded that age does not explain the variation in DRWR across sectors, we exclude it from the remaining models. The other insignificant variable is profit elasticity, but it is only marginally insignificant (with p-value of 0.12). Model C3 suggests that this may be due to its correlation with the capital-labour ratio. Indeed, as shown in Table 1, the profit elasticity is higher, i.e. competition is stronger, in less capital-intensive sectors. The significant variables in Model C1 have the predicted sign and the values of the coefficients are of the same order of magnitude as in Table 4.

Model C1 may also be affected by endogeneity of profit elasticity. In Appendix A in the section that discusses the estimation of profit elasticity, we show that profit elasticity might depend on marginal costs (our example is based on a simple Cournot model). Since DRWR may influence wage dynamics, it also affects costs and thereby the profit elasticity and causes simultaneity in our regression model. We account for the potential simultaneity bias by estimating Model C2 with instrumental variables for profit elasticity. We use the following instruments for profit elasticity: the Herfindahl index, number of firms per branch (and year) and the relative net increase in the number

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[14] See Card and de la Rica (2006), Cardoso and Portugal (2005), Dell'Aringa and Lucifora (1994), Gerlach and Stephan (2006), Hibbs and Lock (1996), Palenzuela and Jimeno (1996) and Rycx (2003) for Belgium.

[15] The wage level and bonuses are highly collinear with the other variables included in the equation. Regressing the earnings level on the remaining explanatory variables excluding bonuses yields a coefficient of determination of 0.67; while the R^2 for the regression of bonuses on the other variables without the earnings level reaches 0.81.

of firms in each branch and year. The model is estimated by two-stage least squares.[16] In Model C4, the coefficient on profit elasticity increases and becomes significant when compared to Models C1 and C2. On the other hand, the capital-labour ratio loses its significance. The estimates of the remaining coefficients are broadly in line with the previous estimates.

Table 5 - Explaining differences in DRWR across sectors, composite models

Dep. var. $DRWR_{jt}$ Est. method	Model C1 OLS	Model C2 OLS	Model C3 OLS	Model C4 2SLS
age_{jt}	0.017			
	(1.24)			
$blue\text{-}collars_{jt}$	-0.001*	-0.001*	-0.001	-0.002**
	(-1.85)	(-1.73)	(-1.52)	(-2.14)
$size_{jt}$	-11.012*	-10.764*	-11.833**	-14.900**
	(-1.88)	(-1.83)	(-1.98)	(-2.28)
K/L_j	-0.011***	-0.012***		-0.072
	(-2.62)	(-2.77)		(-1.40)
Profit $elasticity_{jt}$	0.023	0.021	0.041***	0.049**
	(1.65)	(1.49)	(3.44)	(2.13)
SE $coverage_j$	-0.002*	-0.002	-0.002**	-0.001
	(-1.74)	(-1.28)	(-2.06)	(-1.18)
Constant	0.091	0.685***	0.381***	0.465**
	(0.18)	(4.95)	(4.42)	(2.33)
Year dummies	yes	yes	yes	yes
Sector dummies	no	no	no	no
R^2_{adj}	0.254	0.252	0.220	0.233
Number of obs.	173	173	173	173
F test for excluded instruments equal to 0				31.831
[p-val.]				[0.000]
Sargan's χ^2 test				2.875
[p-val.]				[0.238]

Notes: In Model C4, profit elasticity is treated as an endogenous variable. It is instrumented with the following excluded exogenous variables: Herfindahl index, number of firms per branch (and year) and the relative net increase in the number of firms in each branch and year.

age_{jt} is the average age of workers;
$blue\text{-}collars_{jt}$ is the percentage of blue-collar workers;
$size_{jt}$ is the average size of firms, measured in thousands of employees;
K/L_j is the capital-labour ratio, measured in thousands of euro;
SE $coverage_j$ is the percentage of blue-collar workers covered by single-employer collective agreements
*/**/*** indicate significance at the 0.10, 0.05 and 0.01 level, respectively.
t-statistics in brackets.

In order to highlight the importance of each variable for the variation of DRWR across sectors, Figure 2 reports the contribution of each variable to sector-specific DRWR (averaged over all years) based on Model C4.

16 We run several tests of validity of our set of instrumental variables. First, the F-test for joint significance of the excluded exogenous variables in the first stage equation confirms that the instrumental variables are partially correlated with profit elasticity, the endogenous variable (see Table 5). Second, the insignificant test statistic of the Sargan's test of overidentifying restrictions states that the instruments are uncorrelated with the structural error term.

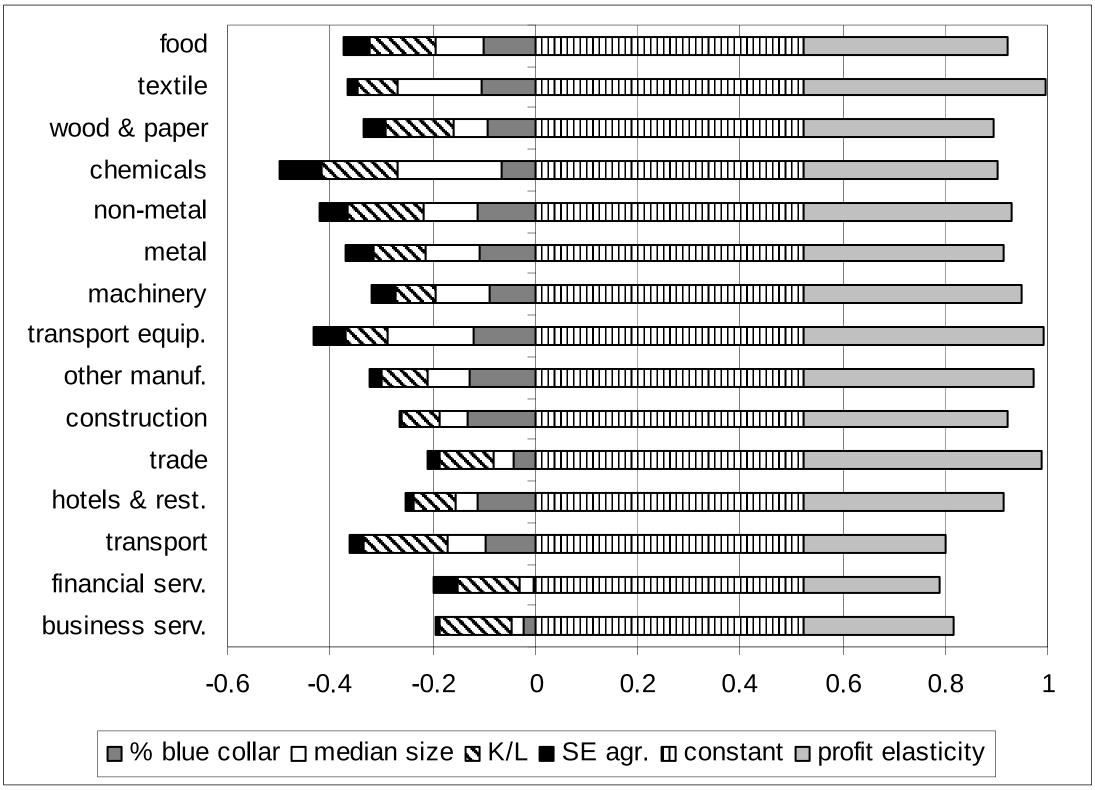

Figure 2 - Decomposition of DRWR based on Model C4 in Table 5 (average across years)

Figure 2 shows that the constant picks up a large part of the DRWR in all sectors. This is consistent with the view that national institutions drive most of the observed wage rigidity. In particular, full automatic indexation and collectively agreed real wage increases are natural potential factors of real wage rigidity.[17] The value of the constant is in line with the observations made in Section 3.1. The standard deviation of DRWR across sectors is 0.19, around the mean of 0.58 (see Table 2).

Leaving the constant aside, Figure 2 highlights the role of the different variables in explaining variation in DRWR across sectors. Let us first compare construction and chemicals, sectors that show the highest and one of the lowest values of DRWR in Table 2 (0.80 and 0.47, respectively). This gap may be attributed essentially to a big difference in capital intensity, firm size and SE agreement coverage. As shown in Table 1, the chemical industry has one of the highest capital-labour ratios, the highest median firm size and the highest SE agreement coverage, while the opposite holds true for construction. As suggested by our estimates in Table 5, the higher the values of these variables, the lower the DRWR. These factors explain why DRWR is much higher in construction than in chemicals, despite the fact that construction has a disproportionately high percentage of blue-collar workers, while chemicals has an average proportion of blue-collar workers in its workforce.

[17] This statement cannot be tested in the framework of this study. The role of national institutions may be better evaluated by a cross-country analysis, as in Dickens et al (2006) or the meta-analysis of Clar et al. (2007).

In the services sector, financial and business services have similar degrees of DRWR (0.63 and 0.67, respectively) and both sectors employ a very high proportion of white-collar workers. In spite of these similarities, they differ in that business services are characterised by higher capital intensity and financial services by higher SE agreement coverage.

Figure 1 shows that most DRWR is common to all sectors, and that variations across sectors are largely due to factors such as workforce composition, production technology (capital intensity) and the degree of competition on the product market. Our results also indicate that labour-intensive sectors have more rigid wages, which backs up the argument that price stickiness observed in labour-intensive sectors is due to wage rigidity. Importantly, our results point up the role of firm-level wage bargaining in dampening wage rigidity, although Figure2 reveals that this accounts for only a small fraction of DRWR.

4. Conclusion

Wage rigidity has important consequences at both the microeconomic and macroeconomic level. When wages are rigid, they no longer evolve hand in hand with productivity developments and interfere with efficient allocation of resources. Downward wage rigidity is considered as one of the causes of unemployment and price stickiness in Europe. It also bears implications for the design and effectiveness of monetary policy. These findings have led to wide empirical literature on the evaluation of wage rigidity, based on macroeconomic, sector-level or, more recently, microeconomic data. The driving factors behind wage rigidity have seldom been investigated, but a better understanding of them can be gained simply by comparing the situation in different countries or sectors, for example.

This paper examines whether differences in wage rigidity across sectors can be explained by differences in workforce composition, competition, technology and wage-bargaining institutions. Given the institutional features of the Belgian labour market, and particularly its system of full automatic indexation, and considering previous findings by Du Caju et al. (2007), nominal wage rigidity seems to be of little relevance. We have therefore focused on downward rigidity of real wages, adopting the measure of downward real wage rigidity developed by Dickens and Goette (2006). The estimates are based on a large administrative matched employer-employee dataset for Belgium over the period 1990-2002. We have also used sector-level information derived from firms' annual accounts over the same period and the 1999, 2000, 2001 and 2002 waves of the Belgian Structure of Earnings Survey (SES).

Our results are derived from two sets of exercises. First, downward real wage rigidity has been estimated for different categories of workers (defined according to their occupation and age category), year and sector. We then formally tested differences in DRWR across worker types. We ran a regression for our estimates of DRWR as a dependent variable on worker-type dummies as independent variables, as well as on elements of the individual firms' pay policy such as the level of bonuses and earnings. Our results indicate that DRWR is significantly higher for white-collar workers and younger workers. Further worker categories with higher earnings and bonuses are characterised by lower DRWR, conditional on their occupation and age category.

Second, we have focused solely on the variation in DRWR across sectors. Our estimates of DRWR show that there are substantial differences in DRWR across sectors. DRWR ranges from 0.35 in transport and storage and less than 0.50 in the chemicals and non-metal industries to 0.80 in construction. Along with variables related to workforce composition, we have included explanatory variables that can be suggested as determinants of DRWR, such as capital intensity, firm size, competition and an index for decentralised wage bargaining measured by the percentage of firms with firm-level agreements. All these variables have then been combined into a single model. We find that wages are more rigid in smaller firms and in more competitive sectors (measured by profit elasticity). Our results also suggest that DRWR is greater in labour-intensive sectors. Lastly, the impact of labour market institutions on DRWR has been taken into consideration as a way of capturing the decentralisation of wage bargaining. Our findings suggest that sectors with more centralised wage formation (i.e. with lower firm-level agreement coverage) have higher DRWR. Given the predominant role of sector-level collective wage bargaining in wage-setting practices in Belgium, this indicates that firm-level collective agreements tend to enhance wage flexibility by taking closer account of firm-specific situations in wage determination.

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Appendix A: Data

This appendix discusses the definitions of variables employed in the paper. The subscripts used refer to the particular group of observations over which the variable varies. The shortcuts for branch, occupation, age category and year are *j*, *k*, *a* and *t*, respectively. Unless explicitly stated, the variables come from the same administrative database on individual labour earnings for Belgium collected by the social security system used in Du Caju et al. (2007). Our trimming procedure for annual gross earnings is explained in Section 2 of the paper. In addition, we use information from firms' balance sheets. Finally, we also rely on individual data from the Belgian Structure of Earnings Survey (SES), for the 1999, 2000, 2001 and 2002 waves.

Wage rigidity measure

The administrative employer-employee dataset provides individual information on annual gross earnings (including bonuses) and annual working days. We evaluate DRWR from the distribution of the changes in the log of annual earnings divided by the number of work days of full-time job stayers.

Variables related to compensation

Variables related to firms' pay policy are the level of earnings and the level of bonuses. Earnings refers to daily gross earnings of an employee and are defined as annual gross earnings in euro divided by the annual number of work days. Bonuses are obtained from the SES and refer to annual bonuses of an employee expressed in euro. We do not make use of the variation of bonuses over years in order to retain as many observations as possible (our main dataset covers the period 1991-2002, and the SES 1999-2002 only).

Firm size

We measure firm size by the number of employees. The definition of the number of employees in the balance sheet has changed over the period under examination. Since 1996 (and in some cases 1997), firms have reported the total number of employees at the end of the year. Before 1996, only information on the average number of employees per year is available. Variables denoted as "Employees < 25_{jt}" and "Employees > 499_{jt}" refer to the percentage of firms in each branch and year that employ less than 25 and more than 499 employees, respectively.

Capital-labour ratio

Firm-level capital-labour ratios are computed for all firms, both public companies and non-profit associations, which publish annual accounts for a full year from January to December. The capital stock is computed on the basis of the perpetual inventory method:

$$P^I_{st}K_{it} = (1-\delta_i)P^I_{st-1}K_{it-1}(P^I_{st}/P^I_{st-1}) + P^I_{st}I_{it}$$

with K_{it} representing the real capital stock, P^I_{st} the sector-specific gross capital formation deflator and δ_i the firm-specific depreciation rate. The initial nominal capital stock is given by the book accounting value of the capital stock, plus revaluation gains, minus depreciation and amounts writte-downs. The firm-specific depreciation rate was estimated as the median depreciation of expenditure on capital, over the years in which the firm is in business. Labour is defined as the number of employees, as above. Capital to labour ratios are taken as the median or average within each sector over the entire period 1991-2002 and are measured in euro. We do not consider the capital-labour ratio by year, because, in the short run, changes in the ratio can reflect employment changes rather than a change in the production technology.

As a robustness test, we calculate the capital-labour ratio from the national accounts data too. We take the net capital stock per sector at the end of the year divided by the yearly average of the number of workers in the branch of activity. In national accounts, the gross capital stock is estimated according to the perpetual inventory method, based on historical series of gross fixed capital formation, the average service life of fixed assets and survival functions, from which the cumulative value of consumption of fixed capital is deducted to obtain the net stock. We deflate the net capital stock using the sector-specific gross capital formation deflator at the A31 level.

Competition measures

We use a relatively new measure of competition, proposed by Boone et al. (2007), namely the elasticity of firms' profits with respect to marginal costs. A higher value of this profit elasticity suggests more intense competition. The intuition is as follows. An increase in costs lowers the firm's profits. As firms in less competitive markets have some market power over their prices, a given percentage increase in costs will lead to a smaller decline in profits than for firms in more competitive markets.

As shown in their paper, under monopoly conditions, the profit elasticity is a positive linear function of the demand elasticity. Consider a monopoly facing a constant elasticity demand function $x=p^{-\varepsilon}$, where x is output, p the output price and $-\varepsilon$ the price elasticity of demand. With c, the marginal cost, the firm's profit is given by $\Pi=x^{(\varepsilon-1)/\varepsilon}-cx$. Profit maximisation with respect to output yields the following expressions for output, $x=(\varepsilon-1)^{\varepsilon}/(\varepsilon c)^{\varepsilon}$, and profits, $\Pi=((\varepsilon-1)^{\varepsilon-1}/\varepsilon^{\varepsilon})c^{-(\varepsilon-1)}$. Taking the expression in logs yields $\ln\Pi=\ln((\varepsilon-1)^{\varepsilon-1}/\varepsilon^{\varepsilon})-(\varepsilon-1)\ln c$. The profit elasticity is equal to $-(\varepsilon-1)$.

Profit elasticity might also depend on marginal costs. To illustrate this, we consider the standard Cournot model with two firms and linear demand curve in the form $p(x_1,x_2) = a - b_1x_1 - b_2x_2$, where x_i is the output produced by firm *i*, the size of the market is captured by *a*, and b_i is each firm's own elasticity of demand. The cost function of each firm takes the form of $C(x_i) = c_i x_i$. Firm *i* chooses its output x_i so that it maximises its profits:

$$\max_{x_i}\{(a-b_1x_1-b_2x_2)x_i-c_ix_i\} \qquad i=\{1,2\} \tag{a1}$$

In addition, we assume that $a > c_i > 0$ and that $b_i > 0$. Solving (a1) yields a reaction function of firm *i* to the output of firm *j*

$$x_i(x_j)=\frac{a-b_jx_j-c_i}{2b_i} \tag{a2}$$

In a Nash equilibrium, both firms are choosing best response to their competitor's output choice. After substituting x_j in equation (a2) by $x_j(x_i)$, we obtain the equilibrium output of each firm

$$x_i^* = \frac{a + c_j - 2c_i}{3b_i}$$

This can be substituted into the profit function to obtain the equilibrium profits

$$\Pi_i^* = \frac{\left(a + c_j - 2c_i\right)^2}{9b_i}$$

and we can show that each firm's profit elasticity is a non-linear function of marginal costs

$$\frac{\partial \Pi_i^*}{\partial c_i}\frac{c_i}{\Pi_i} = -\frac{4c_i}{a + c_j - 2c_i} \qquad \text{(a3)}$$

If DRWR has an impact on wages, it also influences profit elasticity through equation (a3), causing simultaneity in our regression models. In Model C4 in Table 5, we use instrumental variables to account for potential simultaneity bias. See also Boone (2000) and Boone et al. (2007) for other examples and more general model specifications.

To estimate the profit elasticity, we follow Boone et al. (2007). More specifically, we regress the log of profits on the log of marginal costs. Marginal variable costs are defined as variable costs over turnover and are denoted as "mc" in what follows. We use information on all profit-maximising firms that file annual accounts for the whole year from January to December. We identify outliers as firms with variable costs over turnover below or above the 5^{th} and 95^{th} percentile of the distribution and we use the same criterion for profits over total assets. For each branch of activity, we estimate the following regression with firm-specific fixed effects for the period 1991-2002:

$\ln \pi_{it} = \alpha_i + \gamma_t - \beta_t \ln mc_{it} + \varepsilon_{it}$,

where β_t is the profit elasticity and π stands for profits.

As a robustness check, we also use the Herfindahl index as a simple measure of competition within each branch and year. We start by calculating the sum of the squares of the market shares of each individual firm within the branch. Market share is defined as the proportion of a firm's value added in the total value added of the branch. Finally, we re-scale the index to range from 0 to 1. Formally, it is computed as

$$H_b = \frac{\sum_{i=1}^{N_b}\left(VA_i \big/ \sum_{i=1}^{N_b} VA_i\right)^2 - 1/N_b}{1 - 1/N_b},$$

where VA_i is the value added of firm i in branch b, and N_b is the number of firms in branch b. As a measure of concentration, a small value of the Herfindahl index indicates a competitive industry with no dominant players.

We also consider the sector-level estimates of price-cost margins constructed by Christopoulou and Vermeulen (2007) for NACE 2 sectors for the US and several EU countries, including Belgium. The estimates are time-invariant. In cases where our sector definition is more aggregated than theirs, we consider the simple average of their estimated mark-ups.

Table A1 reports the three measures of competition as well as correlations with median firm size in the sector, the number of firms within the industry, the firms' entry and exit rates.

Table A1: Competition measures

	Profit elasticity	Herfindahl index	Price Cost Margin
food	7.957	0.014	1.08
textile	9.514	0.009	1.09
wood and paper	7.436	0.007	1.13
chemicals	7.809	0.029	1.16
non-metal	8.514	0.023	1.15
metal	8.119	0.036	1.13
machinery and equip.	8.642	0.023	1.20
transport equipment	9.877	0.074	1.06
other manufacturing	9.159	0.005	1.08
construction	8.432	0.001	1.17
trade	9.821	0.003	1.22
hotels and restaurants	8.189	0.013	1.23
transport and storage	5.784	0.010	1.26
financial services	5.473	0.012	1.44
business services	6.007	0.003	1.78
Mean	8.049	0.018	1.21
Standard deviation	1.388	0.019	0.18
Correl. with number of firms	-0.46	-0.22	0.70
Correl. with firm entry rate	-0.08	-0.42	0.64
Correl. with firm exit rate	-0.07	-0.42	0.63
Correl. with firm size	0.46	0.63	-0.55

Note: Correlation coefficients are calculated for sectors included in the dataset.

Single-employer (SE) agreement coverage

The information on SE agreements is obtained from the Structure of Earnings Survey (SES) for Belgium covering the period 1999-2002 with annual frequency. The dataset contains separate indicators of SE agreements for blue-collar and white-collar workers at the firm level and this allows us to match the data with the occupational categories in our paper. For instance, for blue-collar workers, the SE agreement coverage refers to the percentage of this category in each sector that work in firms with SE agreements covering blue-collar workers.

Appendix B: Robustness

In this appendix, we consider the robustness of our results along three dimensions. Section B1 considers the sensitivity of our estimates to alternative definitions of the variables under study. Section 2.3.2 discussed potential problems related to the estimation of equations (1) and (2) by the OLS technique. In Section B2, we consider whether the OLS estimates suffer from misspecification error related to the fact that our dependent variable is constrained to take values only on the interval [0,1]. First, we test whether the predicted values of the dependent variable (DRWR) lie outside the [0,1] interval. Next, we apply Ramsey's (1969) regression error specification test. Finally, we present estimation results based on alternative technique that takes into account the bounded nature of the dependent variable. More specifically, we adopt the quasi-maximum likelihood method (QML) developed by Papke and Wooldridge (1996). Section B3 corrects standard errors of the OLS estimates for the presence of intra-class correlation within sectors, as discussed in Section 2.3.2.

B1 Robustness with respect to definitions of competition on the product market

In Table B1, we consider robustness of the regression models C1, C2 and C3 presented in Table 5 with respect to the measure of competitiveness, i.e. we replace profit elasticity by the Herfindahl index and by the estimated mark-ups reported in Vermeulen and Christopoulou (2007). In Models C1B and C2B in Table B1, the coefficient on the Herfindahl index is negative, implying that more concentrated industries have a lower degree of DRWR. The coefficient is insignificant in Model C1B but it is significant in Model C2B at the 10 percent level. The predicted effect reflects our findings based on profit elasticity, i.e. more competitive sectors have higher DRWR. However, the Herfindahl index coefficient becomes insignificant and with reverse sign once the capital-labour ratio is excluded. Estimates with the mark-up also deliver mixed results. The mark-up coefficient is not significant and its sign depends on the inclusion of capital intensity.

One may argue that the profit elasticity may be a more reliable measure of competition, among others, when increased competition leads to market concentration. However, our estimates in Tables 5 and B1 indicate that the relationship between product market competition and wage rigidity is not robust to alternative definitions of competition, and should therefore be treated with caution.

Table B2 - Robustness of models S1 and S2 in Table 5 with respect to Herfindahl index

Dep. var. $DRWR_{jt}$	Model C1B	Model C2B	Model C3B	Model C1C	Model C2C	Model C3C
Est. method	OLS	OLS	OLS	OLS	OLS	OLS
age_{jt}	0.010			0.014		
	(0.74)			(1.02)		
$blue\text{-}collars_{jt}$	-0.001	-0.001	-0.000	-0.001	-0.001	-0.000
	(-1.19)	(-1.14)	(-0.27)	(-0.81)	(-0.85)	(-0.26)
$size_{jt}$	-7.036	-7.061	-4.295	-7.463	-7.630	-4.188
	(-1.28)	(-1.29)	(-0.74)	(-1.34)	(-1.37)	(-0.72)
K/L_j	-0.177***	-0.180***		-0.150***	-0.151***	
	(-4.40)	(-4.52)		(-4.14)	(-4.18)	
$Herfindahl_{jt}$	-1.574	-1.708*	0.312			
	(-1.51)	(-1.67)	(0.32)			
Price Cost $Margin_{jt}$				0.022	0.007	-0.027
				(0.15)	(0.05)	(-0.17)
SE $coverage_j$	-0.001	-0.000	-0.004***	-0.002	-0.002	-0.004***
	(-0.43)	(-0.07)	(-2.61)	(-1.52)	(-1.19)	(-2.61)
Constant	0.533	0.879***	0.601***	0.341	0.838***	0.641**
	(1.12)	(10.36)	(9.70)	(0.62)	(3.38)	(2.50)
Year dummies	yes	yes				
R^2_{adj}	0.252	0.254	0.162	0.241	0.241	0.162
Number of obs.	173	173				

Notes:

age_{jt} is the average age of workers;
$blue\text{-}collars_{jt}$ is the percentage of blue-collar workers;
$size_{jt}$ is the average size of firms, measured in thousands of employees;
K/L_j is the capital-labour ratio, measured in thousands of euro;
SE $coverage_j$ is the percentage of blue-collar workers covered by single-employer collective agreements
*/**/*** indicate significance at the 0.10, 0.05 and 0.01 level, respectively.
t-statistics in brackets.

B2 Accounting for bounded dependent variable

To test whether the bounded nature of the dependent variable causes misspecification of the OLS model, we first consider whether the predicted dependent variable in the OLS models lies within the natural limits of DRWR, i.e. the [0,1] interval. Indeed, we find that this is the case for all models considered in the paper. Second, we use the general test for specification error (RESET) proposed by Ramsey (1969). The test is based on the idea that if we add to our regression higher powers of the independent variables or the predicted dependent variable, all these variables should be jointly insignificant. Otherwise, there is a specification error present in our original model. For most of the models considered in the paper, the RESET test is inconclusive. Using higher powers of the predicted dependent variable, we are almost always unable to reject the null hypothesis that the model has no omitted variables, implying that the linear model fits the data well. On the other hand, the version of the RESET test that adds higher powers of the independent variables to the model always rejects the null hypothesis, suggesting model misspecification.

To emphasise our point, we consider the following generalised linear model

$$g\{ E(y) \} = X\beta, \qquad y \sim \text{Bernoulli} \tag{3}$$

where y is the dependent variable following Bernoulli distribution and $g\{\cdot\}$ is a logit function. This specification was suggested by Papke and Wooldrige (1996), who estimate such a model with quasi-maximum likelihood method (QML). Tables B2 to B4 provide estimates of the same models as Tables 3 to 5 in the main text using the QML method instead of OLS. In line with the conclusion of the RESET test, we find that the coefficient estimates by OLS and QML are very similar.

Table B2 - DRWR per year, occupation, age category and sector, QML estimates, cf. Table 3

Dep. v. $DRWR_{kajt}$	Model (1)	Model (2)	Model (4)	Model (3)
D white-$collar_{kajt}$	0.071***	0.087***	0.135***	0.112***
	(4.05)	(5.21)	(5.17)	(5.10)
D age:$25\text{-}44_{kajt}$	-0.052**	-0.060***	-0.022	-0.023
	(-2.40)	(-2.77)	(-0.88)	(-0.92)
D age:$45+_{kajt}$	-0.033	-0.048**	0.006	0.017
	(-1.42)	(-2.04)	(0.22)	(0.58)
$bonus_{kaj}^{\dagger}$			-0.031***	
			(-2.97)	
$earnings_{kajt}^{\dagger}$				-1.850***
				(-2.87)
Year dummies	yes	yes	yes	yes
Sector dummies	no	yes	no	no
Number of obs.	758	758	758	758

Notes: The table presents marginal effects of the QML estimates.
† measured in thousands of euro.
*/**/*** indicate significance at the 0.10, 0.05 and 0.01 level, respectively.
t-statistics in brackets.

Table B3 - Sector-specific factors affecting DRWR, QML estimates, cf. Table 4

Dep. var. $DRWR_{jt}$	(1)	(2)	(3)	(4)	(5)
age_{jt}	-0.022*	-0.007	-0.012	-0.021*	0.016
	(-1.87)	(-0.55)	(-1.01)	(-1.81)	(1.10)
blue-$collars_{jt}$	-0.000	0.001	-0.002**	-0.001	-0.000
	(-0.41)	(0.72)	(-2.32)	(-1.58)	(-0.75)
$size_{jt}$		-14.063***			
		(-3.16)			
K/L_j			-0.018***		
			(-5.81)		
Profit $elasticity_{jt}$				0.030***	
				(2.65)	
SE coverage					-0.005***
					(-4.16)
Year dummies	yes	yes	yes	yes	yes
Sector dummies	no	no	no	no	no
Number of obs.	173	173	173	173	173

Notes: The table presents marginal effects of the QML estimates.
age_{jt} is the average age of workers;
blue-$collars_{jt}$ is the percentage of blue-collar workers;
$size_{jt}$ is the average size of firms, measured in thousands of employees;
K/L_j is the capital-labour ratio, measured in thousands of euro;
SE $coverage_j$ is the percentage of blue-collar workers covered by single-employer collective agreements
*/**/*** indicate significance at the 0.10, 0.05 and 0.01 level, respectively.
t-statistics in brackets.

Table B4 - Explaining differences in DRWR across sectors, composite models, QML

Dep. var. $DRWR_{jt}$	Model C1	Model C2	Model C3
Est. method	QML	QML	QML
age_{jt}	0.017		
	(1.17)		
$blue\text{-}collars_{jt}$	-0.001*	-0.001	-0.001
	(-1.72)	(-1.64)	(-1.47)
$size_{jt}$	-11.391**	-11.168**	-12.354**
	(-2.13)	(-2.13)	(-2.37)
K/L_j	-0.011***	-0.012***	
	(-2.94)	(-3.17)	
Profit $elasticity_{jt}$	0.025*	0.022	0.044***
	(1.71)	(1.57)	(3.41)
SE coverage	-0.003*	-0.002	-0.003**
	(-1.88)	(-1.57)	(-2.43)
Year dummies	yes	yes	yes
Sector dummies	no	no	no
Number of obs.	173	173	173

Notes: The table presents marginal effects of the QML estimates.
age_{jt} is the average age of workers;
$blue\text{-}collars_{jt}$ is the percentage of blue-collar workers;
$size_{jt}$ is the average size of firms, measured in thousands of employees;
K/L_j is the capital-labour ratio, measured in thousands of euro;
SE $coverage_j$ is the percentage of blue-collar workers covered by single-employer collective agreements
*/**/*** indicate significance at the 0.10, 0.05 and 0.01 level, respectively.
t-statistics in brackets.