Heterogeneous labor demand: sectoral elasticity and trade effects in the U.S., Germany and Sweden.

Judzik, Dario

MTEySS, UB

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Dario Judzik†

MTEySS - UB‡

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Abstract

This paper analyzes labor demand at the sector level in the U.S., Germany and Sweden in two ways: by providing new computations of the sector elasticity of labor demand, and by evaluating the employment effects of trade in manufactures, services, agriculture and fuel. We compute the elasticity through a standard fixed-effects model (i.e., under the assumption of full coefficient homogeneity) and then by taking a semi-pooling sector-level approach (i.e., by flexibilizing the homogeneity assumption). The results reveal that most sector-level elasticities differ largely from the aggregate estimate in all three countries. Also, the sector elasticity values are generally higher in the U.S. and Sweden than they are in Germany. Among the most flexible sectors are the IT sector in the U.S. and Germany, as well as manufacturing in Germany and Sweden, and the mining and energy sectors in the U.S. and Sweden. On the other hand, the employment effect of openness to trade is generally positive, although it varies according to country-level differences. We also mesure technical change to find that it is similar in the U.S. and Sweden, and small or inexistant in Germany, which may help in understanding its remarkable employment performance over the last decade.

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†E-mail: dariojudzik@gmail.com

‡Ministerio de Trabajo, Empleo y Seguridad Social (Argentina) and Universidad de Belgrano.

1 Introduction

To what extent are labor markets flexible (or not)? Should they be further flexibilized? The recent worldwide economic crisis caused high unemployment levels (10.2% in the Euro area and 9.0% in the U.S. in 2011) and aroused the standard economic policy advice of labor market flexibilization. This advice is based on the classical idea that wage rigidity over the market clearing level does not let unemployment to cool down, and has been used to argue, for example, that more flexible labor markets recover faster from financial crises (Bernal-Verdugo *et al.*, 2012). Another strand of the literature, however, dissents from this mainstream view by stressing that recent data shows that the U.S. "flexible jobs machine" may be failing relative to other "less flexible" economies like Germany (Freeman, 2013).

Whatever the case, the achievement of a certain level of unemployment is the result of the aggregation of employment dynamics (jobs creation and destruction) in each economic sector. In this context, in case of sectoral heterogeneity, for a fine tuning of policy design it is crucial to identify these differences.

In a recent contribution, Young (2013) provides new estimates of the elasticity of substitution between labor and capital (σ) in the U.S. at the industry level. He argues that σ differs significantly across industries which creates heterogeneous responses to economic policy. For example, a tax policy that increases the user cost of capital will affect disproportionately the demand for capital where σ is larger. Hence, the focus on sector-level employment is vital for a better understanding of labor market outcomes.

This paper analyzes labor demand at the sector level in the U.S., Germany and Sweden from two perspectives. First, we provide and contrast new computations of sector labor-demand as well as the aggregate labor demand elasticities (ε). Second, we differentiate the effect of trade on employment by four types of merchandises: manufactures, services, agriculture and fuel.

We argue that sector-level mechanisms are essential to labor market outcomes and usually concealed behind aggregate results. The heterogeneity in ε at the sector level is a measure of the unbalanced effects on employment of any potential labor market policy or shock. These diverse effects call for sector-level tailoring of labor market policy, at least as a complement to economy-wide ways of action. The dependence of labor market dynamics on the institutional setting is frequently mentioned in the literature and calls for country-level study and comparability. Accordingly, the analysis in this paper takes a step further than Young (2013) by providing international comparison between economies representative of three different labor market types.

According to Slaughter (2001) the importance of measuring the elasticity of labor demand relies on three main pillars. First, the higher the elasticity of labor demand, then new labor costs (like higher payroll taxes) have a proportionally higher effect on labor than it does on firms. Second, a higher elasticity implies a higher sensitivity of employment to any exogenous shock to wages or labor demand. And third, with a higher elasticity labor has lower bargaining power over rent distribution, and thus a declining labor income share is expected. Hence, policy addressed to increase the employment elasticity, allegedly intended to lower unemployment, may have backfire effects for workers and households. The decline of labor income share over labor market deregulation and trade liberalization are issues covered in Judzik and Sala (2013) and Stockhammer (2013).

We also examine the employment effects of higher openness to trade in manufactures, services, agriculture and fuel. Both aspects relate closely since there is evidence that labor market flexibility has increased in recent decades because of the higher exposure to international trade (e.g. Slaughter 2001, Hijzen and Swaim 2010), although less efforts have been devoted to analyzing the influence of international trade on the number of workers employed using sector level data.

We contribute to this literature by tackling the following question: how does further openness to international trade affect employment? The relevance of this question relies in the fact that employment consequences of international trade are still an unresolved issue (see, for example, Rueda-Cantuche *et al.,* 2013; and Jansen and Lee, 2007). Jansen and Lee (2007) stress that "the only general conclusion that may be justified is that employment effects depend on a large number of country-specific factors" (ibid, p. 30), which again calls for individual-country analysis. Furthermore, we contribute by extending the analysis to the whole economy. The same authors also argue that most existing studies of trade and employment refer to manufacturing employment, which leaves most of the economy unattended (manufactures represented in 2010 about 12% of total value added in the U.S., 19% in Sweden and 22% in Germany).

Our analysis is performed in an intermediate level of aggregation known as a semi-pooling approach (Nunziata, 2005; Heinz and Rusinova, 2011). We estimate a pooled model under the usual assumption of full coefficient homogeneity, and also by applying a semi-pooling approach conceived as an intermediate stage of aggregation between full homogeneity and the other extreme (i.e. individual time-series estimation for each cross-section). This intermediate level of aggregation allows us to find labor-demand elasticities not only for the aggregate economy, but also at the sector-level in each country, while also benefiting from the efficiency gains of pooling control variables.

The analytical framework for our empirical analysis is based on two steps. First, we present a standard formulation of sectoral labor demand where employment in each sector depends on standard factors such as sectoral average real wage, sectoral value added, openness to trade and a time trend proxying technical change. Second, we compute the output-constant labor-demand elasticity (Hamermesh, 1993) for nine sectors (as defined by the ISIC Revision 4) in the U.S., Germany and Sweden.

The model includes the degree of openness to trade as a determinant of employment following previous research. Its inclusion serves as a control variable aiming at a better estimation of the wage-coefficient in the employment equation and, additionally, it allows the analysis of the effect of trade openness on domestic employment at the sector level. On a further step, we disaggregate the effects of openness to international trade on sectoral employment in four types of merchandise: manufactures, services, agriculture and fuel. This exercise provides information on which types of trade are more beneficial or detrimental for the evolution of employment in each country.

Our results confirm that the heterogeneity in sector labor-demand elasticity is usually disguised under the common-coefficient assumption imbedded in standard panel data estimations. In other words, the estimated values of sector elasticity of labor demand run in significantly wider ranges than the values found from an aggregate perspective in all three countries. The sector elasticity values are generally higher in the U.S. and in Sweden than they are in Germany.

If we rank sectors according to their estimated labor demand elasticity, some sectors are repeatedly among the higher ranked values. For example, the IT sector in the U.S. and Germany, manufacturing in Germany and Sweden, and the mining and energy sectors in the U.S. and Sweden. In contrast, the retail trade sector has the lowest elasticities in the U.S. and Germany, together with the finance services sector in Germany and Sweden. Notably, in our results we do not observe general criteria in terms of manufacturing having lower or higher elasticity than services sectors at this level of disaggregation. In sum, a one-fits-all approach to labor market policy will probably be inefficient since it will have very dissimilar results depending on economic activities and country (or institutional setting).

Regarding openness, a larger exposure to trade is associated with an impulse on employment in the U.S. and Sweden, but not in Germany. This is consistent with our finding of higher sector labor-demand flexibility in the U.S. and Sweden than in Germany. Exposure to international trade tends to increase labor market flexibility and, according to this result, trade has a stronger effect on labor market dynamics in the U.S. and Sweden.

When looking into different types of merchandise, although openness to trade in manufactures has also an accelerating effect on employment in both the U.S. and Sweden as expected, a higher level of trade in services has a positive effect on employment in Sweden and a negative impact in the U.S. We believe that the role of services industries in each of these countries, plus service offshoring and its skill-biased effect on domestic employment may provide possible explanations. In line with recent research, we identify and mesure technological change. Our estimations assert that employment is affected by labor-saving technical change. This effect is similar in Sweden and the U.S., and tiny or inexistent in Germany. This result may help in explaining the better performance of Germany's employment growth over the last decade.

The rest of the paper is structured as follows. Section 2 presents a bird-eye view of stylized facts regarding employment structure and openness to trade. Section 3 provides the analytical framework. Section 4 stresses the econometric methodology and empirical strategy, and section 5 presents and discusses the results. Finally, section 6 concludes.

2 Stylized characterization of sectoral employment and trade exposure in the U.S., Germany and Sweden.

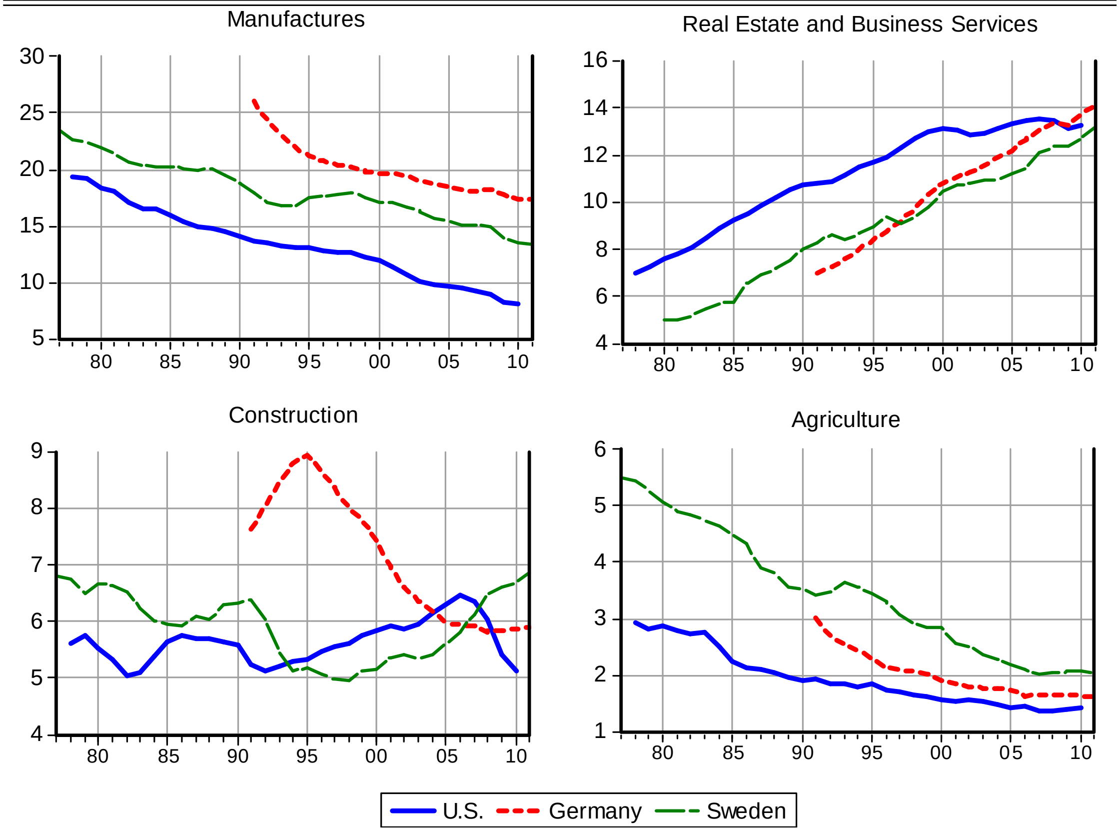
We study the cases of the U.S., Germany and Sweden as industrialized economies with diverse labor market structures and exposures to international trade. Regarding the institutional setting of the labor market, these three countries represent examples of three frequently cited categories of labor market structure according to their tax and welfare systems (e.g. Daveri and Tabellini, 2000): the Anglo-Saxon (U.S.), the Continental Europe (Germany) and the Nordic (Sweden) setting.

At the aggregate level, these three economies had different labour market performances over the last few decades, specially after 2008. Germany introduced major labor market reforms between 2003 and 2005 (so-called Hartz reforms) that included new strong employment policy and services, a reduction in long-term unemployment with new incentives for job searching, and deregulation of fixed-term contracts to stimulate labor demand. These reforms contributed to Germany's resilience to the Great Recession (Rinne and Zimmermann, 2013) and went further than mere flexibilization.

As put by Freeman *et al.* (2010), "the Swedish economic model is perhaps the most ambitious and publicized effort by a capitalist market economy to develop a large and active welfare state" (ibid, p. 1). Sweden suffered a strong economic crisis in the first part of the 1990s from which recovered with strong policy reforms concerning flexible exchange rates and inflation targeting for stronger currency and export-led growth, contraction of the public sector, reduced generosity in social insurance systems, and deregulation in product markets (Freeman *et al.*, 2010). The recession that started in 2008 in the U.S. had similar causes than the 1990s crisis in Sweden (deregulated financial markets and bubble burst in asset pricing transmitted from banks to the whole economy). This time around, perhaps, Sweden was better prepared.

But when looking at sector-level behavior, sectors have evolved in different ways. The U.S. and Sweden have become more service-oriented economies whereas in Germany manufactures and construction represent more important parts of the economy. Figure 1 presents the evolution of employment of selected sectors in the U.S., Germany and Sweden.

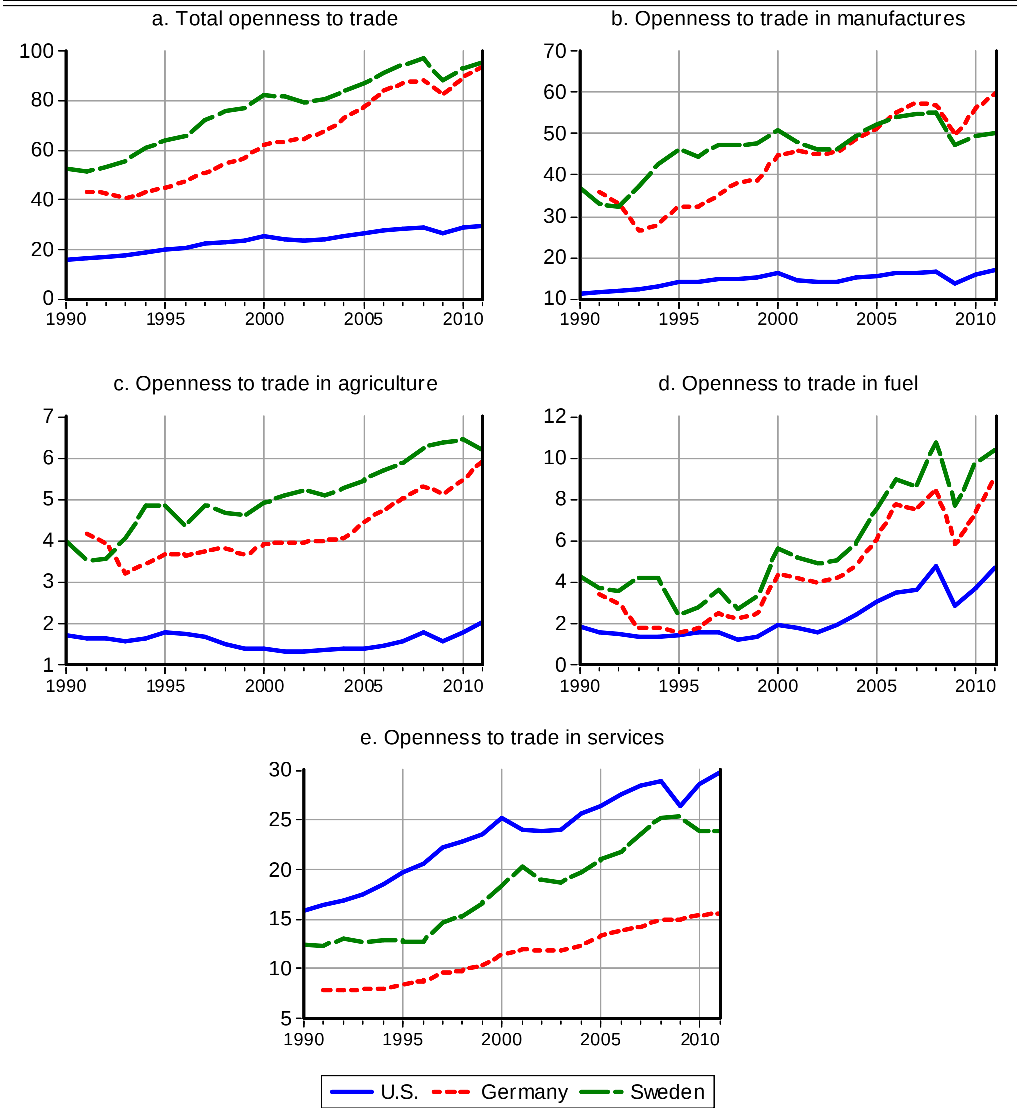
Figure 1. Sectoral employment (% of total employment).



The percentage of employment allocated in manufactures is higher in Germany than in Sweden and the U.S., but it has declined in all three since the 1980s. In turn, the real estate and business services sector employs an increasing proportion of workers. Note that at the last available observation, in Germany there is still a higher percentage of employment in manufactures than in real estate and business services (17.4% and 14.1% respectively), in Sweden it is almost the same (13.4% and 13.2%), while in the U.S. the proportion of employment in manufactures is now lower than that of the real estate and business services sector (8.2% and 13.5%). This structural change in sector-level employment has been the object of study in several works (e.g. Schettkat and Yocarini, 2006).

Structural change has not arrived everywhere. In all three countries the retail trade and financial services sectors have not increased significantly the proportion of employment over the last decades. The U.S. has the highest proportion of sectoral employment in both sectors, Sweden has the lowest, and Germany is an intermediate case. Retail trade represents more than 20% of employment in all three countries, while finance and insurance services still represent less than 5% of total employment.

Figure 2. Degree of openness to international trade (%).



On the other hand, these three economies have different degrees of exposure to international trade. The rate of total trade (exports plus imports) over GDP is a frequently used proxy of the degree of openness to international trade. It is of around 30% in the U.S., 94% in Germany and 95% in Sweden (data of 2011). In this sense the former is a lesser open economy and the two latter are much more open ones (Figure 2, plot a). The degree of openness in the U.S. had a flat evolution since 1990, while it doubled (or nearly doubled) in Germany and Sweden.

These aggregate values, however, do not tell the whole story. For example, Germany and Sweden display a high degree of trade openness in manufactured goods, while trade of manufactures over GDP is less than 20% in the U.S. (plot b). In contrast, the U.S. has the highest level of trade in service industries, closely followed by Sweden, while Germany has a lower third place (plot e).

We believe that these differentiated labor market structures and performance, combined with diverse experiences in employment across sectors (Figure 1), plus also differentiated trade exposures (Figure 2) call for a sector-level computation of the elasticity of labor demand. Different industries have diverse hiring and firing dynamics and, hence, sector labor demand elasticity computations may provide new information than the usual aggregate labor demand elasticity. Moreover, individual-country analysis should be judged appropriate considering that employment responsiveness is conditional on the institutional structure of each economy and a one-fits-all policy cannot be properly tailored.

3 Analytical framework

3.1 A sector labor demand model

We follow Young (2013), who includes industry subscripts to the CES production function with factor-augmenting technological change *à la* Antràs (2004) and McAdam and Willman (2013). This scheme represents the behavior of the representative firm for each industry instead of the representative firm for the aggregate economy.

Accordingly, consider a CES production function where the representative firm in sector i in period t produces real output Q following:

$$Q_{it} = \left[\theta_i (A_t^N N_{it})^{-\beta_i} + (1-\theta_i)\left(A_t^K K_{it}\right)^{-\beta_i}\right]^{-1/\beta_i}, \tag{1}$$

where K = capital stock and N = employment; A_t^N and A_t^K are time-varying coefficients of technological change; A_t^N proxies labor-augmenting (Harrod-neutral) technical change and A_t^K proxies capital-augmenting (Solow-neutral) technical change; $\sigma = \frac{1}{1+\beta}$ is sector i constant elasticity of substitution between capital and labor and θ_i is sector i constant coefficient of factor share ($0 < \theta < 1$).

- **The sector demand for labor**

A profit-maximizing firm in a competitive environment will employ labor so that the marginal productivity equals the real wage rate:

$$\frac{\partial Q_{it}}{\partial N_{it}} = MPL_{it} = W_{it} \tag{2}$$

where W = real wage rate and MPL = marginal productivity of labor. According to (2), deriving from (1) we find that:

$$W_{it} = \theta_i (A_t^N)^{-\beta_i} (Q_{it})^{1+\beta_i} (N_{it})^{-(1+\beta_i)} \tag{3}$$

Solving for N:

$$N_{it} = (\theta_i)^{\frac{1}{1+\beta_i}} (W_{it})^{\frac{-1}{1+\beta_i}} (A_t^N)^{\frac{-\beta_i}{1+\beta_i}} Q_{it} \tag{4}$$

and log-linearizing we find an employment equation representation of a marginal productivity condition:

$$n_{it} = \sigma_i \log \theta_i - \sigma_i w_{it} + q_{it} - (1 - \sigma_i) \log A_t^N \tag{5}$$

where $n = \log(N)$, $w = \log(W)$ and $q = \log(Q)$.

Following the hypothesis in Antràs (2004) we assume that labor efficiency grows at a constant rate and A_t^N is determined as follows:

$$A_t^N = A_0^N e^{\lambda_N . t} \tag{6}$$

where t is a time trend, λ_N is the constant rate of labour-augmenting efficiency growth and A_0^N is the initial value of the efficiency coefficient.

Moreover, we include openness to trade for two reasons: as a control variable (since there is evidence that trade liberalization affects the elasticity of labor demand) and to analyze its effect on employment. Then further disaggregation in four types of merchandise provides information on what sort of trade is more or less favorable to domestic employment in the three economies studied.

Hence, (5) can be re-expressed as:

$$n_{it} = \alpha_i - \sigma_i w_{it} + q_{it} - (1 - \sigma_i)\lambda_N t + \lambda_{op} op_t \tag{7}$$

where $\alpha_i = \sigma_i \log \theta_i - (1 - \sigma_i) A_0^N$ is a cross-section specific intercept. Equation (7) is the baseline equation. It presents the time-evolution of employment in each sector as determined by: a cross-section intercept, the average real wage in that sector, the sectoral output or value added, a time trend as a proxy for technical change, and the degree of openness to international trade. Note that the coefficient associated to the real wage is the sector-level constant elasticity of substitution between labor and capital.

- **The output-constant elasticity of labor demand**

Following Hammermesh (1993) we compute the output-constant elasticity of labor demand at the sector level using the estimated elasticity of substitution between labor and capital (σ_i) from the model described above. The Hicks-Allen elasticity of substitution was defined as changes in relative factor price on relative inputs of the two factors, holding output constant. That is:

$$\sigma = \frac{d\ln(K/N)}{d\ln(w/r)} = \frac{d\ln(K/N)}{d\ln(F_K/F_N)} = \frac{F_N.F_K}{Y.F_{NK}} \tag{8}$$

where $F(K, N)$ is a generic production function, r is the user cost of capital and $F_N = w$ and $F_K = r$ under the assumption of a competitive environment.

Then Hamermesh (1993) defined the own-wage elasticity of labor demand (with output and cost of capital constant) as:

$$\varepsilon_i = -(1 - s_i)\sigma_i \tag{9}$$

where s_i is labor's share in sectoral value added and subscript i represents each sector. Note that in (9) output is kept constant but the capital-labor ratio is allowed to vary as the relative price of production factors changes. Each ε_i is computed with the estimated σ_i from our empirical model and the average s_i from the data . Thus, the computed sector elasticity depends on the relative availability of capital in that sector and the elasticity of substitution. The sectors where labor represents a lower share of income are associated with a higher elasticity of labor demand. Likewise, a higher elasticity of substitution makes labor more easily substitutable by capital, and this also implies a higher elasticity of labor demand.

3.2 Discussion

Our functional form for aggregate production [equation (1)] is equivalent to equation (1) in Young (2013). In this way, we follow a broad strand of the literature that deals with the modeling of the aggregate production assuming a CES functional form along the lines of Arrow *et al.* (1961). The employment equation obtained is a productivity condition derived from the optimization of aggregate production.

In what follows we discuss two main issues regarding the functional form of sector labor demand [equation (7)]: the interpretation of the estimated coefficients and the treatment of technological change.

First, it is important to stress that it is a mistake to interpret the coefficient of real wage as an output-constant elasticity of demand, since by equation (7), it is actually σ. According to Hamermesh (1993), the output-constant elasticity of labor demand is the elasticity of substitution between labor and capital adjusted by the capital share of total income. If a Cobb-Douglas technology of production is assumed, the elasticity of substitution between labor and capital is one, the labor share of income around 0.66, and the elasticity of labor demand around -0.33. But when flexibilizing the aggregate production to take a CES form, the long-run coefficient associated to the real wage is the elasticity of substitution between labor and capital. The crucial point is that this elasticity can be estimated instead of assumed to be unity.

Hence, the substitutability between capital and labor is at the core of the elasticity of labor demand with respect to the real wage. As stressed by Rowthorn (1999), economics based on Cobb-Douglas production functions (with $\sigma = 1$) implies that an increase in real wages generated by investment in new capital leads to a loss of employment on existing equipment, which is enough to offset entirely the extra jobs created on new equipment, and therefore capital investment cannot increase employment in the long run. There is large evidence that the elasticity of substitution between capital and labor is significantly lower than one, specially in the U.S. (e.g., Klump *et al.,* 2012; Chirinko *et al.,* 2011; Leon-Ledesma *et al.,* 2010; and Chirinko, 2008).

Second, once an aggregate production is modeled through a CES production function, there is a choice between Hicks-neutral or factor-augmenting technical change. On this account, we follow Acemoglu (2003), Antràs (2004) and McAdam and Willman (2013), among others, in adopting a factor-augmenting approach. This allows for the identification of factor-biased technical change and the mesure of its incidence, instead of undertaking, for example, the *a priori* assumption of Hicks neutrality. This literature is relatively new, and estimates a significant labor-saving effect of technological change in the U.S. (Klump *et al.*, 2012).

Lastly, the functional form of the sector employment equation must reflect the fact that exposure to trade affects labor market outcomes. Recent evidence points in the direction that higher trade intensity affects employment (e.g., Gozgor, 2013; and Yanikkaya, 2013).

4 Econometric methodology and empirical strategy

This section discusses the methodological aspects of our endeavor. The choices that determine those aspects are made in correspondence to the type of data and empirical objectives of this study.

The next subsections present how we follow recent literature in dealing with the critical issues faced by related research. The first part is standard: we select estimation methods appropriate for our database and empirical model. Second, regarding the issue of cross-section heterogeneity, we argue in favor of a semi-pooling approach as our empirical strategy. We understand as a semi-pooling approach an intermediate stage between full parameter homogeneity (that is, one constant coefficient for all cross-sections, the most common approach to panel data) and the individual cross-section estimations for all variables in time-series models. In this paper, a semi-pooled regression refers to the estimation of individual cross-section coefficients for key variables to this study and homogenous coefficients associated to control variables.

4.1 Estimation methodology

The choice of estimation methodology in panel-data macroeconomic models is not trivial. Usually, panel data estimations are designed for a large cross-section dimension (N) and a few time periods (T). Moreover, some underlying assumptions are based on the fact that the many N homogeneous cross-sections are randomly selected out of a much bigger population (e.g., individuals, households or firms). In this scenario, to model with common coefficients for all cross sections is efficient and advisable.

In our case, we have three panels with $N = 9$ sectors that cover the whole economy, and the maximum availability of time-periods. These are panels with $T > N$ where the homogeneity assumption does not hold. When the database is a pool of short time-series, where each one constitutes a cross-section unit with a strong personality like countries or sectors, the standard panel data models may not be the best fit.

A common practice is the inclusion of fixed-effects (FE, i.e. cross-section specific intercepts) to control for some degree of baseline heterogeneity (that is, constant heterogeneity through time). Not only this control for heterogeneity is not enough in our case, but also the OLS with FE model presents a bias in dynamic specifications as shown in Nickell (1981) and henceforth known as Nickell bias. This bias may be reduced when T is high, which it is so in our panels.

Another issue comes along the inclusion of the lagged endogenous variable for the explicit modeling of dynamics in sector employment: it introduces the impossibility to hold the OLS assumption of strict exogeneity of the regressors. Regarding this issue, an instrumental variable method should be considered to avoid the menace of endogeneity bias.

Pooling time-series together introduces new problems related to the spherical errors assumption. While cross-sectional errors may be homoscedastic and non auto-correlated, the pool has new issues, because homokedasticity is required across both dimension. When having cross-section units with strong personality as in our case (economic sectors) it is likely that cross-section residuals will have different variances and thus the panel will be heteroscedatic across N. Also, since they are sectors of the same economy (and country) they have common unobservable variables, so that the disturbances are presumably correlated.

The related literature deals with these issues by using the panel-corrected standard errors (PCSE) suggested by Beck and Katz (1995) and Beck (2001), the feasible generalized least squares estimator (FGLS) and instrumental variables (Gnagnon 2013; Zhu 2013).

The OLS estimation with PCSE, while still assuming same-unit homokedasticity as the usual time-series models, corrects for contemporaneous correlation of common unobservables and inter-unit heterokedasticity (the so-called "panel heterokedasticity") caused by the pooling of several time-series (Beck and Katz, 1995). Therefore the PCSE is a robust standard error approach for cross-unit dependence (Zhu, 2013).

Moreover, the standard FGLS is a highly used method among the studies with $T > N$ panels (e.g. Heinz and Rusinova, 2011). Instrumental variables are included to control for the potential endogeneity of the dynamic modeling as well as for the fact that real wage may not be exogenous to employment (Lewis and McDonald, 2002). Then, the second method used is a two-stage FGLS with instrumental variables (TS-FGLS). Recent contributions like Young (2013) also add instrumental variables to the GLS framework for the same reason. Cross-section weights are included to control for cross-sectional heterokedasticity.

4.2 To pool or not to pool?

A standard modelization under full cross-section homogeneity would give biased estimations. Many argue that this assumption rarely holds in non-randomized observational studies (Zhu, 2013). The heterogeneity bias that arises from estimating constant coefficients for all cross-sections in a heterogeneous dynamic panel model persists regardless the number of cross-section dimensions, time periods and choice of instrumental variables (Pesaran and Smith, 1995). Moreover, cross-section units that respond to sectors or countries rather than individuals or firms are likely to be heterogeneous. It follows that an effective control for heterogeneity must be examined.

The fixed-effects (FE) model controls for baseline unobserved heterogeneity with a cross-section specific intercept. In a dynamic heterogeneous model the FE approximation, which imposes coefficient homogeneity (i.e., identical slopes for all cross-section units), may give inconsistent estimations (Steiner, 2011). A dynamic heterogeneous panel model needs to take into account the different responses of sector employment to changes in the main variables. But even if the FE model was not biased we would be estimating an "average" slope. So we need to ask ourselves: is this useful to our empirical objective? One can easily find, for example, a "not significant" slope (i.e. statistically zero) when actually every cross-sectional slope is non-zero, but as they are"summed up" they cancel out each other (Juhl and Lugovskyy, 2013).

At the opposite end, there is the random coefficient model where both intercept and all estimated coefficients vary across economic sectors (i). This model entails the estimation of numerous coefficients thus requires large panel dimensions (degrees of freedom). For that reason this model may not be adequate for our database.

It is a main concern in panel data analysis how much to pool. For the reasons described we must consider an intermediate degree of pooling between the full-homogeneity assumption and the individual coefficient estimation for all intercepts and variables included in the model. Juhl and Lugovskyy (2013) argue that the specification of a "partially heterogeneous" model where some variables share a common slope and others are allowed to be heterogeneous is a viable solution for the pooling issue.

In our model of sector employment, cross-section units consist on nine sectors that clearly present an heterogeneous behavior (see Figure 1), as studied by the structural change literature. Nunziata (2005) faces a similar challenge in a wage-setting study where cross-sections are countries with institutional heterogeneity. He argues that the pooled model yields more efficient estimates than the country by country regression, but the poolability test results are not robust enough to justify a pure coefficient homogeneity framework. In his view, this situation calls for an intermediate degree of poolability that allows for some degree of heterogeneity (at least in key variables), in a pooled data framework that gains efficiency from a common estimation of control variables. This procedure reduces the potential bias from assuming full homogeneity in actually heterogeneous models.

Ultimately, our objective is to find reliable estimates for the elasticity of substitution between production factors at the sector level (σ_i). It would be our preference to perform sector-level time-series estimations, but we come across the lack of large annual time series in several sectors as an inexorable shortcoming. As in Nunziata's case, we need to explore an intermediate degree of pooling that improves the degrees of freedom from the lack of large sector-level time series and at the same time, that allows for cross-section specific estimations of the main coefficients. Zhu (2013) stresses that pooling different time series together while accounting for cross-section heterogeneity can compensate the lack of extended annual data.

As argued by Beck and Katz (2007), there are relatively few attempts like Nunziata (2005) to go beyond the limited heterogeneity provided by the fixed-effects model. They argue that the degree of pooling should be a scientific decision, and then intermediate situations should be explored. Heinz and Rusinova (2011) also decide to pool together the observations for all countries using panel estimation but allowing for differential slopes. They argue that if there are reasons for expecting heterogeneous behaviour, this technique could substantially reduce the potential bias introduced by the homogeneity restriction.

This paper uses both methodologies and contrasts the full aggregation of the data with a semi-pooling approach where individual cross-section coefficients are estimated for the key variables. In particular, for those required for to the estimation of the elasticity of substitution between capital and labor. The other control variables included in the model share common coefficients to all cross-sections. This system "borrows strength" by estimating only one homogeneous coefficient for control variables and keeping cross-section heterogeneity in the main interest variables: real wage and persistence coefficient (lagged employment). Then we can compute the elasticity of labor demand (with respect to the real wage) for each sector while also gaining efficiency by estimating common coefficients associated to the control variables (value added, openness to trade, and time trend).

4.3 Data

Regarding the data, this paper employs OECD STAN sector-level data including nine sectors following the two-digit ISIC Revision 4 classification: (1) agriculture, hunting, forestry and fishing, (2) mining, energy and waste management, (3) manufacturing, (4) construction, (5) wholesale and retail trade, transportation and storage, accommodation and food service activities, (6) information and communication, (7) finance and insurance activities, (8) real estate and business activities, and finally (9) community, social and personal services. Table 2 defines the variables used in the empirical analysis.

The sample availability for the United States is 1978-2010 for five industries. The others are 1988-2010 for community services, 1989-2010 for retail trade, 1998-2011 for mining and energy, and 2000-2010 for information and communication. For Germany the availability is a balanced sample for the 1993-2011 period. For Sweden, the availability of data is 1970-2011 for agriculture, manufactures and construction, and 1993-2011 for all other sectors.

Table 2. Variable definitions and sources of data.

n	Total employment (number engaged)[1].	OECD Stan
w	Labor compensation of employees.	OECD Stan
va	Value added, volume.	OECD Stan
op	Openness to trade (Exports + Imports) / GDP.	OECD Economic Outlook 91
opm	Openness to trade, Manufactures.	WTO and OECD
ops	Openness to trade, Services.	WTO and OECD
opa	Openness to trade, Agriculture.	WTO and OECD
opf	Openness to trade, Fuel.	WTO and OECD
s	Labor income share ($= \frac{W.N}{VA}$).	
t	Time trend.	

Note: all variables are in logs (except s and t).

Aggregate data of international trade (exports and imports) and GDP are national series from the OECD Economic Outlook 91. Disaggregated data on trade of manufactures, agriculture, fuel and services were extracted from the WTO official database. The labor income share (s) for each sector is computed as the ratio of labor compensation over value added.

4.4 Empirical strategy

We estimate equation (7) from different perspectives on the degree of pooling, alternating both estimation methods discussed in the previous section: the panel-corrected standard errors least squares (PCSE) and two-stage feasible generalized least squares with instrumental variables (TS-FGLS). It is crucial to stress that the empirical models are estimated as dynamic equations to take into account the adjustment costs potentially surrounding all variables involved in the analysis (endogenous and exogenous). Also, the signs of the estimated coefficients will be determined empirically: *ex ante* all coefficients are presented with a + sign behind them.

First we assume full homogeneity of the coefficients, only with fixed effects for each cross-section in order to mitigate estimator bias. In this case, the estimated equation takes the form represented by (10).

$$n_{it} = \beta_{0i} + \beta_1 n_{it-1} + \beta_2 w_{it} + \beta_3 q_{it} + \beta_4 t + \beta_5 op_t + \upsilon_{it} \tag{10}$$

where $\beta_{0i} = \alpha_i$ includes a cross-section fixed effect, β_1 is the persistence coefficient, $\beta_2 = \sigma$

[1] Includes full-time, part-time and self-employed.

is the aggregate elasticity of substitution, $\beta_3 = (1-\sigma)\lambda_N$, $\beta_4 = \lambda_{op}$ and υ_{it} is a well-behaved error term.

On a second step, we estimate an augmented equation with a disaggregation in nine sectors, as detailed above.

$$n_{it} = \gamma_{0i} + \gamma_{1i} n_{it-1} + \gamma_{2i} w_{it} + \gamma_3 q_{it} + \gamma_4 t + \gamma_5 op_t + \nu_{it} \tag{11}$$

Note that in equation (11) the coefficients γ_{1i} and $\gamma_{2i} = \sigma_i$, associated to the effect of the real wage on employment, are estimated individually for each sector (for all i). The rest of estimated coefficients, γ_3, γ_4 and γ_5, remain as homogeneous coefficients (under the borrowing strength concept explained previously).

A third and last step includes the disaggregation of total openness to trade in four variables according to the type of merchandise: openness to trade in manufactures (opm), services (ops), agriculture (opa) and fuel (opf). This gives rise to our third empirical model represented by equation (12).

$$n_{it} = \gamma_{0i} + \gamma_{1i} n_{it-1} + \gamma_{2i} w_{it} + \gamma_3 q_{it} + \gamma_4 t + \gamma_5 opm_t + \gamma_6 ops_t + \gamma_7 opa_t + \gamma_8 opf_t + \nu_{it} \tag{12}$$

Combining the empirical models of sector-level employment represented in equations (10), (11) and (12), and the estimation methods explained in the previous section (PCSE and TS-FGLS), we compute the sectoral elasticity of labor demand in the nine industries included in the sample and evaluate the effect of openness to trade on employment.

5 Results

This section presents the empirical results of our study in three subsections. First, we present and discuss the estimated values of σ_i and computed values of ε_i for each one of the three countries studied. Second, we discuss the employment effect of a higher exposure to international trade. Third, we disclose the employment effect of technological change.

Note that in all tables in section 5.1. we abbreviate the sectors as follows: AG for agriculture, hunting, forestry and fishing; ME for mining, energy and waste management; MA for manufacturing; CO for construction; RT for wholesale and retail trade, transportation and storage, accommodation and food service activities; IT for information and communication; FI for finance and insurance activities; RE for real estate and business activities; and SE for community, social and personal services. Additionally, all the estimated equations are available in the Apendix.

5.1 Sector elasticity of labor demand

The results for the U.S. are generally consistent with the values found by Young (2013). He estimates 35 industry-level elasticities of substitution between capital and labor (σ), with three different specifications and three estimation methods. Table 2 compares our results to those of Young (2013), in an adaptation of his industry-level classification to the 9 sectors used in this paper, this is the reason why it is designed with 3 columns presenting, each, a range of values for: the results in our study, Young's preferred method (GMM), and his alternative method that is similar to one of the used in this paper, that he calls three-stage generalized instrumental variables (GIV).

The ranges of values of our estimated elasticities overlap to those of Young (2013). Only the estimated elasticity for the IT sector is outside the range of values found by Young (2013), although the adaptation from his disaggregation in 35 industries to our sectors is not perfect. For example, finance, real estate and insurance services are combined into one industry, whereas the ISIC Revision 4 classification considers two separate sectors, finance and insurance services on the one hand, and real estate services and on the other one.

Table 3. Estimated U.S. sectoral elasticity of substitution (σ_i).

	This study	Young (2013)	
		GMM	GIV
Agriculture (AG)	[0.35 0.52]	[-0.39 0.68]	[-0.09 0.84]
Energy (ME)	[0.62 0.85]	[0.62 0.87]	[0.57 1.64]
Manufactures (MA)	[0.91 1.30]	[0.02 1.41]*	[-0.34 1.26]
Construction (CO)	[0.83 1.12]	[0.32 0.50]	[0.29 1.01]
Retail (RT)	0.49	[0.42 0.60]	[0.11 1.12]
IT Services (IT)	[1.06 1.22]	[0.42 0.48]	[0.57 1.11]
Finance (FI)	[0.54 1.21]	[0.99 1.00]	[0.66 0.92]
Real Estate (RE)	[1.14 3.68]	**	
Community (SER)	< 0	0.39	[-0.02 1.32]

* [0.21 1.10] without leather industry.

** included in finance and insurance.

The estimation of the sectoral elasticity of substitution between capital and labor (σ_i) is an input in the overall analysis in this paper. It is used in the subsequent calculation of the sector elasticity of labor demand (ε_i) which is the central variable of interest. Tables 4, 5 and 6 present the main results for the U.S., Germany and Sweden. In all tables the first column presents the sector labor income share (s_i) computed with the OECD Stan data and used in the calculation of ε_i. In turn, HC denotes homogeneous coefficients, corresponding to the results under the assumption of full coefficient homogeneity [equation (10)].

Table 4. U.S. sectoral labor shares, elasticity of susbstitution and labor demand elasticity.

	1			2		3		4		5	
	PCSE			TS-FGLS		PCSE		TS-FGLS		PCSE	
	s	σ	ε	σ	ε	σ	ε	σ	ε	σ	ε
AG	0.25	0.37	-0.28	0.49	-0.37	0.35	-0.26	0.52	-0.39	0.40	-0.30
ME	0.18	0.85	-0.70	0.62	-0.51						
MA	0.64	0.95	-0.34	1.30	-0.47	0.87	-0.32	1.28	-0.46	0.91	-0.33
CO	0.68	0.98	-0.32	0.83	-0.27	1.12	-0.36	0.80^b	-0.26^b	0.84	-0.27
RT	0.72	0.19^b	-0.05^b	0.49	-0.14						
IT	0.57	1.06	-0.45	1.22	-0.52						
FI	0.56	0.95	-0.41	1.21	-0.53	0.95	-0.42	1.07	-0.47	0.54	-0.24
RE	0.35	1.81	-1.17	2.96	-1.91	1.59	-1.03	3.68	-2.38	1.14	-0.73
SE	0.81	-4.70	*	0.33^b	-0.06^b						
HC	0.61	0.50^a	-0.19^a	0.59	-0.23	0.44^a	-0.17^a	0.33^b	-0.13^b	0.52	-0.20
Sample	1978 2010			1978 2010		1978 2010		1978 2010		1980 2010	
Obs	230			229		165		165		155	

Note: PCSE = Panel-corrected standard errors. TSFGLS = two-stage feasible generalized least squares. No superscript = wage-coefficient significance at 10% level.
^{a} = 0.10 < p-value < 0.15 ^{b} = p-value > 0.15 * = $\varepsilon_i > 0$

In the case of the U.S., specifications 1 and 2 in Table 4 present the unbalanced estimation with all available observations by PCSE and TS-FGLS repectively. Specifications 3 and 4 are performed with a balanced sample of the sectors for which a complete 1978-2010 sample is available. Specification 5 includes the disaggregation of openness to trade, it is also estimated with a balanced sample, and by PCSE. One can see that the values of the estimated sector elasticity of labor demand is broadly robust to a change in estimation methodology, sample (sector selection), and control variables.

The aggregate elasticity of labor demand for the U.S. lies in the -0.23 to -0.17 interval according to our results. Hence, it is likely that the actual value is significantly below the standard Cobb-Douglas assumption of -0.33.

Furthermore, when relaxing this assumption and allowing for sector specific elasticities of substitution, we find that the elasticity of labor demand varies heterogeneously depending on the economic activity. Table 4 shows that 29 out of a total of 33 estimated elasticities are statistically different than zero (at a 15% level).

Take for instance specification 2, which is a two-stage FGLS unbalanced estimation for all sectors. The labor-demand elasticity we find for the real estate and business services sector (RE) is -1.91, far away from the aggregate estimation. But this is the highest value. If we consider manufacturing (MA) or the finance services sector (FI), the elasticities are -0.47 and -0.53 respectively, which is more than twofold the upper-bound aggregate value (-0.23). On the other hand, the estimated value for the retail trade, transportation and accommodation services sector (RT) is -0.14, lower than the aggregate value. The wage coefficient associated to community and social services sector (SE) is non-significant and hence statistically zero.

If we would gather only the homogeneous coefficients (HC) result, we would conclude that the the elasticity of labor demand in the U.S. lies in the -0.23 to -0.17 range, and elaborate labor market policy accordingly. This paper shows that this procedure could be a seriously mistaken, since we would be missing out on the fact that the level of flexibility varies significantly across sectors. Then, labor market policy meant to increase employment could have very dissimilar outcomes. The bottom line is that sector-level analysis has to be taken into account in order to design effective policies.

Tables 5 and 6 present the results for Germany and Sweden, respectively. Both countries have balanced samples in all specifications. In those cases specifications 3, 4 and 5 have a reduced sample of sectors based on the statistical performance in specifications 1 and 2.

The estimation results for Germany and Sweden present similar patterns than those of the U.S. The elasticity of labor demand at the sector level is in fact heterogeneous. Moreover, the values obtained are generally robust to sample period, estimation method and control variables. The same may be said about the ordinal ranking of sectors from the highest to the lowest estimated elasticity. Hence, the findings associated to the results for the U.S. are also robust to applying our empirical model to three different countries, with diverse labor market structures, size and degree of exposure to international trade.

In Germany's case, the HC estimated elasticity of labor demand ranges in the -0.72 to -0.23 interval. In turn, when adopting sector-level computations of the elasticity of labor demand, we find estimated values between -1.07 and -0.04. Taking again specification 2 as an example, the estimated elasticity under HC is -0.72, while the estimated sector labor demand elasticity for the finance services sector (FI) is -0.08 and the one for the retail trade sector (RT) is -0.09, both rather low. This low elasticity of labor demand in the retail sector is also found in the U.S. The most sensitive sectoral labor demand in Germany are agricultural activities (AG), where a 10% increase in the real wage may have a 8% reduction in sectoral labor demand. In general, Germany clearly presents lower ε_i than the U.S. (in absolute value) and in that sense it is in general a less flexible labor market.

Table 5. **Germany** sectoral labor shares, elasticity of susbstitution and labor demand elasticity.

	1			2		3		4		5	
	PCSE			TS-FGLS		PCSE		TS-FGLS		PCSE	
	s	σ	ε	σ	ε	σ	ε	σ	ε	σ	ε
AG	0.29	0.88	-0.62	1.12	-0.80	0.96	-0.68	1.51	-1.07	1.03	-0.73
ME	0.45	1.05	-0.57	-0.10							
MA	0.70	0.66	-0.20	0.89	-0.27	0.68	-0.20	1.06	-0.32	0.69	-0.21
CO	0.75	1.62	-0.40	0.73	-0.18	1.47	-0.36	0.51	-0.12	1.71	-0.42
RT	0.66	0.13^b	-0.04^b	0.27	-0.09	0.06^b	-0.02^b	0.24	-0.08	0.02^b	-0.01^b
IT	0.57	0.25^b	-0.11^b	0.55	-0.24	0.21^b	-0.09^b	0.56	-0.24	0.17^b	-0.07^b
FI	0.66	0.18	-0.06	0.23	-0.08	0.17	-0.06	0.31	-0.11	0.12	-0.04
RE	0.22	0.79^b	-0.62^b	0.39^b	-0.30^b						
SE	0.74	0.68^b	-0.17^b	0.21^b	-0.05^b						
HC	0.58	0.78	-0.32	1.73	-0.72	0.58	-0.24	0.66	-0.27	0.56	-0.23
Sample	1993 2011			1993 2011		1993 2011		1993 2011		1993 2011	
Obs	171			171		114		114		114	

Note: PCSE = Panel-corrected standard errors. TSFGLS = two-stage feasible generalized least squares. No superscript = significance at 10% level. ^{b} = p-value > 0.10

Tables 5 and 6 present the results for Germany and Sweden, respectively. Both countries have balanced samples in all specifications. In those cases specifications 3, 4 and 5 have a reduced sample of sectors based on the performance in specifications 1 and 2.

The estimation results for Germany and Sweden present similar patterns than those of the U.S. The elasticity of labor demand at the sector level is in fact heterogeneous. Moreover, the values obtained are generally robust to sample period, estimation method and control variables. The same may be said about the ordinal ranking of sectors from the highest to the lowest estimated elasticity. Hence, the findings associated to the results for the U.S. are also robust to applying our empirical model to three different countries, with diverse labor market structures, size and degree of exposure to international trade.

$Table6.Swedensectorallaborshares, elasticityofsusbstitutionandlabordemandelasticity.$

	1			2		3		4		5	
	$PCSE$			$TS-FGLS$		$PCSE$		$TS-FGLS$		$PCSE$	
	s	σ	ε	σ	ε	σ	ε	σ	ε	σ	ε
AG	0.29	1.50	-1.06	2.06^b	-1.46^b	0.45	-0.32	0.45^b	-0.32^b	0.45	-0.32
ME	0.28	0.50^a	-0.36^a	0.55^b	-0.40^b	0.59	-0.42	0.56^b	-0.41^b	0.53^a	-0.38^a
MA	0.63	1.74	-0.65	1.30	-0.49	0.48	-0.18	0.77	-0.29	0.52	-0.19
CO	0.81	0.88	-0.17	0.82^b	-0.16^b	1.49	-0.29	1.19	-0.23	1.41	-0.27
RT	0.69	1.18	-0.37	1.77	-0.55	4.67	-1.45	2.10	-0.65	1.13	-0.35
IT	0.64	0.81	-0.29	0.67	-0.24	0.42^a	-0.15^a	1.00	-0.36	0.47^a	-0.17^a
FI	0.46	0.08^a	-0.04^a	0.20^b	-0.11^b	0.04^b	-0.02^b	0.47	-0.26	0.05^b	-0.03^b
RE	0.38	0.37^b	-0.23^b	-2.63	*						
SE	0.89	-1.24	*	-2.46	*						
HC	0.64	0.84	-0.31	0.73	-0.27	0.53	-0.19	0.52	-0.19	0.52	-0.19
$Sample$	19722011			19722011		19952010		19952010		19952010	
Obs	229			225		112		112		112	

$Note: PCSE = Panel-correctedstandarderrors.TSFGLS = two-stagefeasiblegeneralized$ least squares. No superscript = wage-coefficient significance at 10% level.
$^a = 0.10 <$ p-value < 0.15 $\;^b =$ p-value > 0.15 $^* = \varepsilon_i > 0$

5.2 Exposure to international trade

We now turn the attention towards the effect of international trade on employment. As argued by related research, it would be expected that the higher the openness to trade, the higher the labor market flexibility. To control for this phenomenon our specifications include different controls for the degree of openness to trade. In specifications 1 to 4 we include aggregate openness to trade (calculated as the ratio of total trade over GDP). Specification 5 includes a disaggregation of openness to trade in four types of merchandise: manufactures, services, agriculture and fuel.

It is reassuring to find that the computations of ε_i are quite robust to changes in the control for international trade since in specification 5 the estimated values lie around the same values found in the previous specifications (1 to 4) that include only total openness to trade as control.

But the net employment effects of higher openness are still under debate. Trade liberalization has been associated both with job destruction and job creation. It is a rule of thumb that exporting sectors would expand production and their demand for labor, while sectors exposed to competition with imports would reduce production and hence reduce the employment of labor (Jansen and Lee, 2007).

Associated to trade openness is international outsourcing, since balance of payments includes the trade in services. As put by Amiti and Wei (2005), in the past, service sectors were considered virtually unaffected by trade. For example, "accountants did not fear that someone abroad would take their high-paying jobs", but this scenario has changed.

Tables 7 and 8 present the elasticity of the openness to trade variables in our specifications with respect to sector employment. The values in those tables are computed with the homgeneous coefficients estimations (HC). The reason is that the construction of the elasticity requires the openness coefficient plus a global coefficient of persistance. Table 7 shows in each column the elasticity computed from specifications 1 to 4, and table 8 refers to the results from specification 5 that diaggregates openness to trade.

Table 7. Long-run employment impact of international trade.

	1	**2**	**3**	**4**
U.S.	1.86***	-0.02	2.88***	-0.26
Germany	0.15	-0.72*	0.06	0.08
Sweden	1.70***	1.40***	1.17***	0.90**

Note: ***,** and * = significance at 1%, 5% and 10% level.

The degree of openness to international trade has a quite strong positive effect on sectoral employment in Sweden in all specifications (1 to 4; Table 7). The value of the long-run elasticity of this effect lies in the 0.90-1.70 range, thus the exposure to trade in Sweden is likely to be elastic with respect to employment. This positive effect also appears in the U.S., with even higher elasticities (1.86 and 2.88). In turn, the positive employment effect of trade cannot be detected in Germany's case. Not only that, but one specification for the case of Germany (number 2) suggests a negative effect of further openness to trade on employment.

The results for the U.S. and Sweden are consistent with recent evidence. Gozgor (2013), for example, includes four different measures of trade liberalization and globalization in a reduced-form unemployment equation and estimates the parameters for a panel of G7 countries, and all four proxies present a negative and significant effect on equilibrium unemployment. In this context, Germany is an exception, where the exposure to trade has a non-positive effect on employment (that is, a low negative effect, or altogether inextistant).

The disaggregation of the openness to trade variable on to four sectors of merchandise brings further insights (Table 8). Germany still presents no significant effects of openness to trade on employment. The U.S. and Sweden present a robust positive effect on employment of further openness to trade in manufactures, with a similar elasticity than the aggregate case. The case of the degree of exposure to trade in services deserves particular discussion: it has a negative effect on employment in the U.S. and a positive effect in the case of Sweden.

Table 8. Disaggregated employment effect of openness to trade.

	Manufactures	Agriculture	Fuel	Services
U.S.	2.02***	-0.51	0.02	-0.83**
Germany	0.14	0.17	0.05	-0.44
Sweden	1.34***	0.09	-0.17	0.43*

Note: ***,** and * = significance at 1%, 5% and 10% level.

In a recent paper, Yanikkaya (2013) finds that a higher total openness to international trade has a negative effect on the growth rate of industrial employment and a positive effect on the growth rate of service employment. It follows that higher trade intensity may have diverse effects in different sectors.

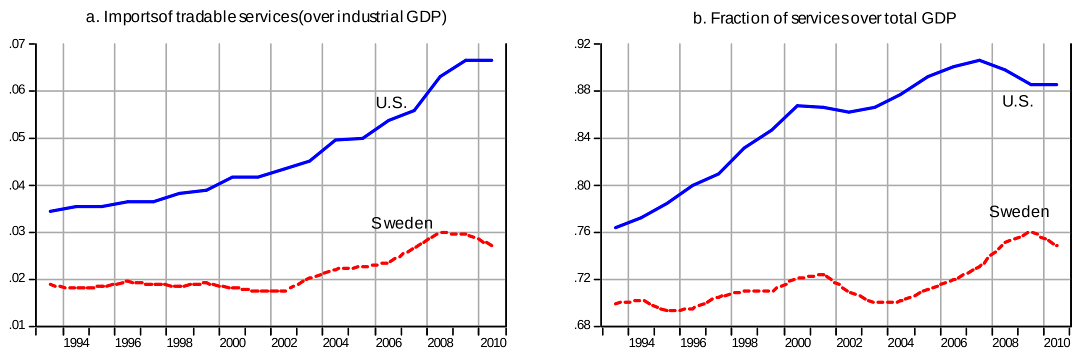
In order to understand the opposite effect of higher trade intensity in services industries on employment in the U.S. and in Sweden we must take a look at what is different between these two countries. Figure 2 (panel e) shows that openness to trade in service industries grew in both countries over the last decades. Nevertheless, it has been always higher in the U.S., especially during the 1990s. Later, this difference has slightly declined (in 2011, openness to trade in services was 30% in the U.S. and 24% in Sweden). Also, most service sectors represented a higher proportion of employment in the U.S. than in Sweden over the sample period, with the exception of the information and communications sector[2].

As aforementioned, in recent years there has been a strong debate over the effect of offshoring (and international outsourcing) on domestic employment. Crinò (2009) presents a complete review of empirical results: Amiti and Wei (2005) find a negative and significant effect of offshoring on employment in an industry-level study for the UK (1992-2000 period), OECD (2007) finds a positive but non-significant effect on employment in 24 industries across 17 OECD countries, and Crinò (2010) estimates the elasticity of service offshoring on domestic employment in 135 occupations in the U.S. over the 1997-2006 period and finds mostly negative effects on low and medium-skilled workers and a slim positive effect on high-skilled worker. The results of Crinò (2010) are consistent with our result for the U.S. The results in OECD's report of 2007 for a panel of 17 countries agree that there may be a positive effect in a given country.

[2] Excluding the public sector (community services).

So the answer must be in the role of service trade in the U.S. and Sweden. Figure 3 presents the ratio of service imports over the industrial GDP (panel a) and the share that services represent on total GDP (panel b). The ratio of U.S. imports of business services over the industrial GDP has grown almost twofold over the 1993-2010 period. In turn, in Sweden this ratio had a flatter evolution, with moderate growth starting only after 2002. These contrasted evolutions combine with the fact that the dimension of the so-called structural change is higher in the U.S. Over the 1990s there was a steep growth of services fraction of GDP in the U.S. while it had a broadly constant evolution in Sweden.

Figure 3: Services in the U.S. and Sweden.



In all, further openness to trade in services in the U.S. can threaten domestic employment, mainly because it could translate in strong growth of imports, continuing the trend depicted over the last decade (Figure 3a). In Sweden, since domestic service industries do not represent as much of total income, and imports of services do not display a strong positive trend, higher levels of trade in services may favor employment.

It is important to recall that the effect of service offshoring is skill-biased and has different effects on high-skilled white-collar, low-skilled white-collar and blue-collar workers (Crinò, 2010). In that sense, certain sectors are more sensitive to openness in services industries than others, bringing different results for different economies depending on their economic structure.

5.3 Technical Change

Finally, we discuss the role of the time trend in all specifications. Recall that the time trend is a standard proxy of a constant-rate technical change. The estimated coefficient associated to the time trend is $(1-\sigma)\lambda_N$ (equations 10, 11 and 12). In almost all specifications $\sigma < 1$, so if the estimated coefficient is negative, then technical change, in the context of the employment model in this paper, would be labor-saving.

Table 9 presents the calculation of the implied coefficient of constant technical change λ_N by our employment equations. It is based on the homogeneous coefficient (HC) estimations since every trend coefficient requires a single σ for the calculation of λ_N. Cells left blank represent that the trend coefficient is not statistically different from zero.

Take for example specification 1 in the U.S: the estimated elasticity of substitution between factors is $\hat{\sigma} = 0.59$, the long-run coefficient of the time trend is -0.07 and then $\lambda_N = 0.166$. So technical change grows at an annual constant rate of 17% and has a labor-saving effect on employment. Labor-saving technical change was already identified for the U.S. by several studies as surveyed by Klump *et al.* (2012), so the direction of the employment effect of technological change may come as no sourprise. Note that in Germany's case, specification 2 has a positive-sign coefficient for the time trend (Table 5), but in that same specification $\hat{\sigma} = 1.7 > 1$ and then the effect is also labor-saving.

Table 9. Growth rate of technical change.

	1	**2**	**3**	**4**	**5**
U.S.	17%		22%		7%
Germany		4%			
Sweden	22%	10%	4%		

Regarding the annual rate of technical change, our employment model yields a range between a 7% and 22% for the U.S., and similar values for Sweden, between a 4% and 22%. In the case of Germany, we find that the time trend is statistically different than zero in only one specification, and the implied value of λ_N is rather low. Then, the annual rate of technical change in Germany is between 0% and 4%.

Note that technical change that proves to be labor-saving in all three countries is either smaller in Germany than in the U.S. and Sweden, or almost inexistent. This result may help in explaining the better performance of employment in Germany over the last decade.

6 Concluding remarks

This paper analyzes the heterogeneity in labor demand from two empirical perspectives. On the one hand, we provide calculations of the sector-level elasticities of labor demand and find that these values vary significantly across economic activities. If we rank sectors according to their estimated labor demand elasticity, some sectors are repeatedly among the most sensitive labor market. For example, the IT sector in the U.S. and Germany, manufacturing in Germany and Sweden, and the mining and energy sectors in the U.S. and Sweden have the most elastict employment effects to changes in labor costs.

In contrast, the retail trade sector has the lowest elasticities in the U.S. and Germany, together with the finance services sector in Germany and Sweden. Notably, in our results we do not observe general criteria in terms of manufacturing having lower or higher elasticity than services sectors at this level of disaggregation.

Policywise, the main implication of these results is that one-fits-all approach to labor market policy will probably be inefficient. The reaction of employment to policy will be quite different depending on economic activities. According to our results, different economic sectors have different sensitivities in their demand for labor. Then, for a better outcome, labor market policy should be properly conciebed taking into account sectoral particularities.

Also, Germany clearly presents lower ε_i than the U.S. (in absolute value) and in that sense it is in general a less flexible labor market. Thus, looking at the performance that both labor markets had during the Great Recession, the following policy question arises: is flexibilization of European labor markets the answer? We join those that call for a rethinking of labor market policy, trying to go beyond labor market flexibilization and regarding issues of investment, technology and productivity.

On the other hand, we investigate the employment effects of higher exposure to international trade. We do this by including the degree of openness to trade in the empirical employment equation, first in its aggregate version, and later disaggregating openness to trade into four variables according to four types of merchandise: manufactures, services, agriculture and fuel. Openness to trade presents a non-negative effect on employment (neutral in Germany and positive in the U.S. and Sweden). But new insights come along disaggregating aggregate openness to trade. Higher trade in manufactures has a positive effect on employment, as expected, in the U.S. and Sweden. Interestingly, a larger degree of openness to trade in services has a negative effect on employment in the U.S. and a positive effect in Sweden.

We believe that this result may be associated to the growing importance of imported services in the U.S. economy and the important role that service industries already play, in contrast to Sweden, where the services share of the economy is still not as large and there may be room to increase trade in services and boost domestic employment. The skill-biased effect of offshoring and international outsourcing is a phenomenon that should be considered.

Lastly, this paper also verifies the presence of labor-saving technical change in the three countries studied. The annual rate of technical change implied by our model of employment is 7% to 22% in the U.S., 4% to 22% in Sweden, and 0% to 4% in Germany.

The fact that this effect is either small or inexistent in Germany may help in explaining its better employment performance over the last decade.

Future research should explore ways to estimate the elasticity of labor demand from the empirical model directly instead of indirectly computing it via the estimated elasticity of substitution. Also, disaggregated effects of openness to trade and technical change for each one of the nine sectors in ISIC Rev. 4 should be undertaken as a methodological challenge.

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APPENDIX

Table A1. United States. Semi-pooled model.

[1] PCSE				[2] TS-FGLS			
c	0.636 [0.290]			c	0.171 [0.863]		
Δn_{t-1}	0.227 [0.003]			Δn_{t-1}	0.333 [0.000]		
Δn_{t-2}	−0.184 [0.027]			Δn_{t-2}	−0.178 [0.005]		
va_t	0.211 [0.000]			va_t	0.301 [0.001]		
t	−0.007 [0.000]			t	−0.001 [0.738]		
op_t	0.179 [0.000]			op_t	0.017 [0.688]		
n_{t-1}^{AG}	0.535 [0.000]	w_t^{AG}	−0.171 [0.000]	n_{t-1}^{AG}	0.538 [0.191]	w_t^{AG}	−0.226 [0.006]
n_{t-1}^{ME}	0.631 [0.000]	w_t^{ME}	−0.314 [0.000]	n_{t-1}^{ME}	0.623 [0.000]	w_t^{ME}	−0.232 [0.012]
n_{t-1}^{MA}	0.697 [0.000]	w_t^{MA}	−0.287 [0.000]	n_{t-1}^{MA}	0.706 [0.000]	w_t^{MA}	−0.384 [0.000]
n_{t-1}^{CO}	0.720 [0.000]	w_t^{CO}	−0.273 [0.011]	n_{t-1}^{CO}	0.616 [0.000]	w_t^{CO}	−0.320 [0.030]
n_{t-1}^{RT}	0.536 [0.000]	w_t^{RT}	−0.086 [0.201]	n_{t-1}^{RT}	0.502 [0.003]	w_t^{RT}	−0.246 [0.053]
n_{t-1}^{IT}	0.860 [0.000]	w_t^{IT}	−0.148 [0.102]	n_{t-1}^{IT}	0.730 [0.031]	w_t^{IT}	−0.329 [0.015]
n_{t-1}^{FI}	0.772 [0.000]	w_t^{FI}	−0.217 [0.000]	n_{t-1}^{FI}	0.706 [0.000]	w_t^{FI}	−0.355 [0.000]
n_{t-1}^{RE}	0.857 [0.000]	w_t^{RE}	−0.260 [0.010]	n_{t-1}^{RE}	0.830 [0.000]	w_t^{RE}	−0.502 [0.000]
n_{t-1}^{SE}	0.845 [0.000]	w_t^{SE}	0.732 [0.001]	n_{t-1}^{SE}	0.714 [0.000]	w_t^{SE}	−0.095 [0.697]
Unbalanced Sample: 1978-2010				Unbalanced Sample: 1978-2010			
Total obs: 230				Total obs: 229			

Notes: p-values in brackets; Instruments: Δn_{t-1} Δn_{t-2} va_{t-1} op_{t-1} t and n_{it-1} w_{it-1} $\forall i$. $c =$ intercept.

Table A2. United States. Semi-pooled model.

[3] PCSE				[4] TS-FGLS			
c	1.017 [0.085]			c	0.040 [0.974]		
Δn_{t-1}	0.268 [0.002]			Δn_{t-1}	0.327 [0.006]		
Δn_{t-2}	-0.218 [0.016]			Δn_{t-2}	-0.190 [0.003]		
va_t	0.209 [0.000]			va_t	0.283 [0.020]		
t	-0.008 [0.001]			t	0.001 [0.841]		
op_t	0.192 [0.000]			op_t	-0.021 [0.705]		
n_{t-1}^{AG}	0.533 [0.005]	w_t^{AG}	-0.163 [0.000]	n_{t-1}^{AG}	0.604 [0.141]	w_t^{AG}	-0.205 [0.013]
n_{t-1}^{MA}	0.685 [0.000]	w_t^{MA}	-0.275 [0.000]	n_{t-1}^{MA}	0.713 [0.000]	w_t^{MA}	-0.367 [0.000]
n_{t-1}^{CO}	0.737 [0.000]	w_t^{CO}	-0.294 [0.008]	n_{t-1}^{CO}	0.652 [0.000]	w_t^{CO}	-0.277 [0.168]
n_{t-1}^{FI}	0.788 [0.000]	w_t^{FI}	-0.202 [0.001]	n_{t-1}^{FI}	0.699 [0.000]	w_t^{FI}	-0.322 [0.001]
n_{t-1}^{RE}	0.862 [0.000]	w_t^{RE}	-0.220 [0.041]	n_{t-1}^{RE}	0.854 [0.000]	w_t^{RE}	-0.538 [0.000]
Balanced Sample: 1978-2010				Balanced Sample: 1978-2010			
Total obs: 165				Total obs: 165			

Notes: p-values in brackets; Instruments: Δn_{t-1} Δn_{t-2} va_{t-1} op_{t-1} t and n_{it-1} w_{it-1} $\forall i$. $c =$ intercept.

Table A3. United States. FE model (HC).

[1] PCSE		[2] TS-FGLS		[3] PCSE		[4] TS-FGLS	
c	0.454 [0.114]	c	0.416 [0.083]	c	0.425 [0.202]	c	0.130 [0.731]
n_{t-1}	0.912 [0.000]	n_{t-1}	0.939 [0.000]	n_{t-1}	0.935 [0.000]	n_{t-1}	0.957 [0.000]
Δn_{t-1}	0.330 [0.000]	Δn_{t-1}	0.520 [0.000]	Δn_{t-1}	0.353 [0.000]	Δn_{t-1}	0.522 [0.000]
Δn_{t-2}	-0.233 [0.005]	Δn_{t-2}	-0.275 [0.000]	Δn_{t-2}	-0.285 [0.003]	Δn_{t-2}	-0.258 [0.004]
va_t	0.072 [0.007]	va_t	0.019 [0.469]	va_t	0.057 [0.060]	va_t	0.023 [0.538]
t	-0.006 [0.000]	t	0.0001 [0.933]	t	-0.008 [0.000]	t	-0.001 [0.815]
op_t	0.163 [0.000]	op_t	-0.001 [0.968]	op_t	0.186 [0.000]	op_t	-0.011 [0.823]
w_t	-0.052 [0.006]	w_t	-0.030 [0.131]	w_t	-0.028 [0.150]	w_t	-0.014 [0.517]
Unbalanced Sample: 1978-2010				Balanced Sample: 1978-2010			
Total obs: 230		Total obs: 229		Total obs: 165			

Notes: p-values in brackets; Instruments in [2] and [4]: n_{it-1} Δn_{t-1} Δn_{t-2} va_{t-1} op_{t-1} t w_{it-1}
c = intercept.

Table A4. United States. Specification [5]. PCSE.

[5] Semi-pooled.				[5] HC	
c	1.366 [0.028]			c	0.191 [0.618]
va_t	0.209 [0.000]			n_{t-1}	0.905 [0.000]
t	−0.002 [0.167]			va_t	0.065 [0.054]
opm_t	0.217 [0.000]			t	−0.003 [0.042]
ops_t	−0.094 [0.008]			opm_t	0.192 [0.000]
opa_t	−0.095 [0.006]			ops_t	−0.079 [0.046]
opf_t	0.008 [0.557]			opa_t	−0.048 [0.147]
n_{t-1}^{AG}	0.471 [0.022]	w_t^{AG}	−0.212 [0.000]	opf_t	−0.002 [0.898]
n_{t-1}^{MA}	0.595 [0.000]	w_t^{MA}	−0.368 [0.000]	w_t	−0.049 [0.031]
n_{t-1}^{CO}	0.624 [0.000]	w_t^{CO}	−0.315 [0.006]		
n_{t-1}^{FI}	0.621 [0.000]	w_t^{FI}	−0.205 [0.002]		
n_{t-1}^{RE}	0.793 [0.000]	w_t^{RE}	−0.236 [0.089]		
Balanced Sample: 1978-2010				Balanced Sample: 1978-2010	
Total obs: 165				Total obs: 165	

Notes: p-values in brackets. c = intercept.

Table A5. Germany. Semi-pooled model.

[1] PCSE				[2] TS-FGLS			
c	0.299 [0.217]			c	0.170 [0.541]		
Δn_{t-1}	0.328 [0.000]			Δn_{t-1}	0.352 [0.000]		
va_t	0.145 [0.000]			va_t	0.206 [0.000]		
t	−0.003 [0.075]			t	0.010 [0.581]		
op_t	0.036 [0.191]			op_t	0.010 [0.743]		
n_{t-1}^{AG}	0.909 [0.000]	w_t^{AG}	−0.080 [0.017]	n_{t-1}^{AG}	0.838 [0.000]	w_t^{AG}	−0.182 [0.000]
n_{t-1}^{ME}	0.918 [0.000]	w_t^{ME}	−0.086 [0.027]	n_{t-1}^{ME}	0.908 [0.000]	w_t^{ME}	0.009 [0.850]
n_{t-1}^{MA}	0.677 [0.000]	w_t^{MA}	−0.213 [0.008]	n_{t-1}^{MA}	0.593 [0.000]	w_t^{MA}	−0.364 [0.000]
n_{t-1}^{CO}	0.863 [0.000]	w_t^{CO}	−0.222 [0.013]	n_{t-1}^{CO}	0.801 [0.000]	w_t^{CO}	−0.146 [0.020]
n_{t-1}^{RT}	0.646 [0.000]	w_t^{RT}	−0.044 [0.522]	n_{t-1}^{RT}	0.483 [0.000]	w_t^{RT}	−0.140 [0.020]
n_{t-1}^{IT}	0.743 [0.000]	w_t^{IT}	−0.064 [0.248]	n_{t-1}^{IT}	0.737 [0.000]	w_t^{IT}	−0.146 [0.020]
n_{t-1}^{FI}	0.658 [0.000]	w_t^{FI}	−0.063 [0.018]	n_{t-1}^{FI}	0.577 [0.000]	w_t^{FI}	−0.098 [0.026]
n_{t-1}^{RE}	0.913 [0.000]	w_t^{RE}	−0.069 [0.679]	n_{t-1}^{RE}	0.876 [0.000]	w_t^{RE}	−0.048 [0.803]
n_{t-1}^{SE}	0.868 [0.000]	w_t^{SE}	−0.091 [0.287]	n_{t-1}^{SE}	0.777 [0.000]	w_t^{SE}	−0.048 [0.523]
Balanced Sample: 1993-2011				Balanced Sample: 1993-2011			
Total obs: 171				Total obs: 171			

Notes: p-values in brackets; Instruments: Δn_{t-1} va_{t-1} op_{t-1} t and n_{it-1} w_{it-1} $\forall i$. c = intercept.

Table A6. Germany. Semi-pooled model.

[3] PCSE				[4] TS-FGLS			
c	0.813 [0.016]			c	0.810 [0.023]		
Δn_{t-1}	0.373 [0.000]			Δn_{t-1}	0.419 [0.000]		
va_t	0.145 [0.000]			va_t	0.297 [0.000]		
t	-0.003 [0.087]			t	-0.002 [0.466]		
op_t	0.053 [0.165]			op_t	0.024 [0.589]		
n_{t-1}^{AG}	0.918 [0.005]	w_t^{AG}	-0.078 [0.037]	n_{t-1}^{AG}	0.839 [0.141]	w_t^{AG}	-0.241 [0.000]
n_{t-1}^{MA}	0.690 [0.000]	w_t^{MA}	-0.210 [0.014]	n_{t-1}^{MA}	0.518 [0.000]	w_t^{MA}	-0.514 [0.000]
n_{t-1}^{CO}	0.854 [0.000]	w_t^{CO}	-0.215 [0.020]	n_{t-1}^{CO}	0.701 [0.000]	w_t^{CO}	-0.151 [0.025]
n_{t-1}^{RT}	0.629 [0.000]	w_t^{RT}	-0.023 [0.772]	n_{t-1}^{RT}	0.220 [0.285]	w_t^{RT}	-0.184 [0.012]
n_{t-1}^{IT}	0.731 [0.000]	w_t^{IT}	-0.058 [0.336]	n_{t-1}^{IT}	0.628 [0.000]	w_t^{IT}	-0.210 [0.004]
n_{t-1}^{FI}	0.618 [0.000]	w_t^{FI}	-0.065 [0.022]	n_{t-1}^{FI}	0.562 [0.001]	w_t^{FI}	-0.137 [0.052]
Balanced Sample: 1993-2011				Balanced Sample: 1993-2011			
Total obs: 114				Total obs: 114			

Notes: p-values in brackets; Instruments: Δn_{t-1} va_{t-1} op_{t-1} t and n_{it-1} w_{it-1} $\forall i$. $c =$ intercept.

Table A7. Germany. FE model (HC).

[1] PCSE		[2] TS-FGLS		[3] PCSE		[4] TS-FGLS	
c	-0.236 [0.130]	c	-1.125 [0.026]	c	-0.022 [0.903]	c	0.042 [0.767]
n_{t-1}	0.906 [0.000]	n_{t-1}	0.824 [0.000]	n_{t-1}	0.853 [0.000]	n_{t-1}	0.832 [0.000]
Δn_{t-1}	0.366 [0.000]	Δn_{t-1}	0.013 [0.945]	Δn_{t-1}	0.367 [0.000]	Δn_{t-1}	0.399 [0.000]
va_t	0.104 [0.000]	va_t	0.289 [0.005]	va_t	0.126 [0.000]	va_t	0.142 [0.001]
t	-0.001 [0.410]	t	0.005 [0.107]	t	-0.001 [0.422]	t	-0.001 [0.518]
op_t	0.014 [0.603]	op_t	-0.128 [0.068]	op_t	0.009 [0.793]	op_t	0.014 [0.771]
w_t	-0.073 [0.000]	w_t	-0.305 [0.009]	w_t	-0.085 [0.001]	w_t	-0.110 [0.001]
Δw_t	0.020 [0.298]	Δw_t	-1.032 [0.040]				
Balanced Sample: 1993-2011				Balanced Sample: 1993-2011			
Total obs: 171				Total obs: 114			

Notes: p-values in brackets; Instruments in [2] and [4]: n_{it-1} Δn_{t-1} va_{t-1} op_{t-1} t w_{it-1} w_{it-2}
c = intercept.

Table A8. Germany. Specification [5]. PCSE.

[5] Semi-pooled.				[5] HC	
c	0.631 [0.112]			c	-0.034 [0.903]
Δn_{t-1}	0.397 [0.000]			n_{t-1}	0.857 [0.000]
va_t	0.145 [0.000]			Δn_{t-1}	0.379 [0.000]
t	0.001 [0.636]			va_t	0.120 [0.000]
opm_t	0.048 [0.176]			t	-0.001 [0.814]
ops_t	-0.121 [0.129]			opm_t	0.020 [0.542]
opa_t	-0.036 [0.333]			ops_t	-0.062 [0.417]
opf_t	0.017 [0.178]			opa_t	0.025 [0.437]
n_{t-1}^{AG}	0.927 [0.000]	w_t^{AG}	-0.075 [0.057]	opf_t	0.007 [0.559]
n_{t-1}^{MA}	0.658 [0.000]	w_t^{MA}	-0.238 [0.015]	w_t	-0.080 [0.002]
n_{t-1}^{CO}	0.862 [0.000]	w_t^{CO}	-0.235 [0.016]		
n_{t-1}^{RT}	0.602 [0.001]	w_t^{RT}	-0.009 [0.925]		
n_{t-1}^{IT}	0.706 [0.000]	w_t^{IT}	-0.050 [0.400]		
n_{t-1}^{FI}	0.559 [0.001]	w_t^{FI}	-0.055 [0.069]		
Balanced Sample: 1993-2011				Balanced Sample: 1993-2011	
Total obs: 114				Total obs: 114	

Notes: p-values in brackets. c = intercept.

Table A9. Sweden. Semi-pooled model.

[1] PCSE				[2] TS-FGLS			
c	-0.398 [0.270]			c	-0.398 [0.483]		
Δn_{t-1}	0.247 [0.000]			Δn_{t-1}	0.217 [0.001]		
va_t	0.248 [0.000]			va_t	0.161 [0.007]		
t	-0.003 [0.002]			t	-0.003 [0.007]		
op_t	0.151 [0.000]			op_t	0.152 [0.005]		
n_{t-1}^{AG}	0.942 [0.000]	w_t^{AG}	-0.086 [0.004]	n_{t-1}^{AG}	0.976 [0.000]	w_t^{AG}	-0.086 [0.004]
n_{t-1}^{ME}	0.678 [0.001]	w_t^{ME}	-0.162 [0.140]	n_{t-1}^{ME}	0.681 [0.010]	w_t^{ME}	-0.162 [0.140]
n_{t-1}^{MA}	0.829 [0.000]	w_t^{MA}	-0.297 [0.000]	n_{t-1}^{MA}	0.831 [0.000]	w_t^{MA}	-0.297 [0.000]
n_{t-1}^{CO}	0.720 [0.000]	w_t^{CO}	-0.245 [0.002]	n_{t-1}^{CO}	0.852 [0.000]	w_t^{CO}	-0.245 [0.002]
n_{t-1}^{RT}	0.706 [0.000]	w_t^{RT}	-0.347 [0.000]	n_{t-1}^{RT}	0.856 [0.000]	w_t^{RT}	-0.347 [0.000]
n_{t-1}^{IT}	0.671 [0.000]	w_t^{IT}	-0.148 [0.102]	n_{t-1}^{IT}	0.731 [0.000]	w_t^{IT}	-0.148 [0.102]
n_{t-1}^{FI}	0.772 [0.000]	w_t^{FI}	-0.217 [0.000]	n_{t-1}^{FI}	0.582 [0.010]	w_t^{FI}	-0.217 [0.000]
n_{t-1}^{RE}	0.857 [0.000]	w_t^{RE}	-0.260 [0.010]	n_{t-1}^{RE}	0.552 [0.125]	w_t^{RE}	-0.260 [0.010]
n_{t-1}^{SE}	0.743 [0.000]	w_t^{SE}	0.732 [0.001]	n_{t-1}^{SE}	0.743 [0.000]	w_t^{SE}	0.732 [0.001]
Unbalanced Sample: 1972-2011				Unbalanced Sample: 1972-2011			
Total obs: 229				Total obs: 225			

Notes: p-values in brackets; Instruments: Δn_{t-1} va_{t-1} op_{t-1} t and n_{it-1} w_{it-1} $\forall i$. $c =$ intercept.

Table A10. Sweden. Semi-pooled model.

[3] PCSE				[4] TS-FGLS			
c	1.639 [0.021]			c	1.635 [0.428]		
Δn_{t-1}	0.242 [0.009]			Δn_{t-1}	0.232 [0.018]		
va_t	0.148 [0.014]			va_t	0.302 [0.010]		
t	-0.007 [0.005]			t	-0.005 [0.080]		
op_t	0.299 [0.000]			op_t	0.283 [0.004]		
n_{t-1}^{AG}	0.699 [0.000]	w_t^{AG}	-0.134 [0.037]	n_{t-1}^{AG}	-0.136 [0.938]	w_t^{AG}	-0.517 [0.458]
n_{t-1}^{ME}	0.633 [0.004]	w_t^{ME}	-0.215 [0.052]	n_{t-1}^{ME}	0.153 [0.805]	w_t^{ME}	-0.478 [0.224]
n_{t-1}^{MA}	0.505 [0.000]	w_t^{MA}	-0.236 [0.000]	n_{t-1}^{MA}	0.505 [0.000]	w_t^{MA}	-0.381 [0.000]
n_{t-1}^{CO}	0.660 [0.000]	w_t^{CO}	-0.506 [0.002]	n_{t-1}^{CO}	0.499 [0.004]	w_t^{CO}	-0.594 [0.007]
n_{t-1}^{RT}	0.938 [0.000]	w_t^{RT}	-0.289 [0.002]	n_{t-1}^{RT}	0.740 [0.010]	w_t^{RT}	-0.545 [0.001]
n_{t-1}^{IT}	0.692 [0.000]	w_t^{IT}	-0.130 [0.148]	n_{t-1}^{IT}	0.641 [0.000]	w_t^{IT}	-0.357 [0.011]
n_{t-1}^{FI}	0.342 [0.094]	w_t^{FI}	-0.024 [0.676]	n_{t-1}^{FI}	0.558 [0.082]	w_t^{FI}	-0.209 [0.059]
Balanced Sample: 1995-2010				Balanced Sample: 1995-2010			
Total obs: 112				Total obs: 112			

Notes: p-values in brackets; Instruments: Δn_{t-1} va_{t-1} op_{t-1} t and n_{it-1} w_{it-1} $\forall i$. c = intercept.

Table A11. Sweden. FE model (HC).

[1] PCSE		[2] TS-FGLS		[3] PCSE		[4] TS-FGLS	
c	0.568 [0.002]	c	0.608 [0.000]	c	1.359 [0.001]	c	1.772 [0.000]
n_{t-1}	0.888 [0.000]	n_{t-1}	0.925 [0.000]	n_{t-1}	0.761 [0.000]	n_{t-1}	0.782 [0.000]
Δn_{t-1}	0.300 [0.000]	Δn_{t-1}	0.263 [0.000]	Δn_{t-1}	0.187 [0.036]	Δn_{t-1}	0.123 [0.180]
va_t	0.062 [0.001]	va_t	0.018 [0.430]	va_t	0.075 [0.080]	va_t	0.014 [0.831]
t	−0.004 [0.000]	t	−0.002 [0.039]	t	−0.004 [0.011]	t	−0.001 [0.621]
op_t	0.190 [0.000]	op_t	0.104 [0.006]	op_t	0.279 [0.000]	op_t	0.196 [0.017]
w_t	−0.094 [0.000]	w_t	−0.055 [0.009]	w_t	−0.127 [0.000]	w_t	−0.113 [0.014]
Balanced Sample: 1995-2011				Balanced Sample: 1995-2011			
Total obs: 112				Total obs: 112			

Notes: p-values in brackets; Instruments in [2] and [4]: n_{it-1} Δn_{t-1} va_{t-1} op_{t-1} t w_{it-1}
c = intercept.

Table A12. Sweden. Specification [5]. PCSE.

[5] Semi-pooled.				[5] HC	
c	1.758 [0.029]			c	1.518 [0.002]
Δn_{t-1}	0.188 [0.062]			n_{t-1}	0.793 [0.000]
va_t	0.150 [0.036]			Δn_{t-1}	0.179 [0.064]
t	-0.004 [0.310]			va_t	0.050 [0.268]
opm_t	0.162 [0.076]			t	-0.001 [0.801]
ops_t	0.142 [0.011]			opm_t	0.278 [0.001]
opa_t	-0.054 [0.456]			ops_t	0.089 [0.089]
opf_t	-0.020 [0.424]			opa_t	0.018 [0.790]
n_{t-1}^{AG}	0.668 [0.000]	w_t^{AG}	-0.150 [0.021]	opf_t	-0.035 [0.158]
n_{t-1}^{ME}	0.680 [0.004]	w_t^{MA}	-0.170 [0.152]	w_t	-0.109 [0.000]
n_{t-1}^{MA}	0.527 [0.000]	w_t^{MA}	-0.245 [0.000]		
n_{t-1}^{CO}	0.677 [0.000]	w_t^{CO}	-0.457 [0.007]		
n_{t-1}^{RT}	0.785 [0.002]	w_t^{RT}	-0.243 [0.018]		
n_{t-1}^{IT}	0.689 [0.000]	w_t^{IT}	-0.146 [0.130]		
n_{t-1}^{FI}	0.334 [0.167]	w_t^{FI}	-0.033 [0.596]		
Balanced Sample: 1995-2010				Balanced Sample: 1995-2010	
Total obs: 112				Total obs: 112	

Notes: p-values in brackets. c = intercept.