Impact of trade liberalization on firm’s labour demand by skill: The case of Tunisian manufacturing

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Abstract

This paper investigates the impact of trade liberalization process in Tunisia on employment by distinguishing different skills and different types of firms using micro level data covering the period 1983-1994. There is considerable disagreement among analysts on the impact of recent trade reforms on labour. Our contribution to these debates in this paper is essentially an empirical issue. The analysis of a Tunisian firms data may be viewed as an attempt to apprehend how employment in Tunisia, a developing country, adjusted to the trade reforms. Using a micro-level detail on individual firms, we are able to trace the relationship between changes in trade policies and manufacturing employment at the firm level and by skill. Although trade reforms are generally implemented at the sector level, their effects may vary significantly across firm characteristics such as ownership (public vs. private) and degree of export orientation. We can then measure the effects of trade policy on employment for different types of firms. We also try to associate changes in employment directly with measure of change in trade protection, rather than link them to changes in imports and exports which is more common.
1. Introduction

Tunisia was one of the countries that abandon import substitution industrialization as a development strategy. Import substitution was designed to protect domestic “infant” manufacturing industries from import through the use of protective instruments, such as tariffs and quotas controls. Since 1986, numerous measures have been taken to further liberalise the trade.

This paper investigates the impact of trade liberalization process in Tunisia on employment by distinguishing different skills and different types of firms using micro level data covering the period 1983-1994.

The basic insight of the H-O model that trade should benefit a country’s abundant factor is quite compelling. More recent episodes of trade liberalization appear not to have been associated with large improvements in prospects for the typical worker (Hasan 2001). The empirical evidence concerning the relationship between employment and trade reform in developing countries is not definitive. Our goal is to highlight some continuing puzzles in our understanding of the effects of trade reform. A possible explanation of the apparent divergence between the expectations of liberalization advocates and the recent evidence is that over the past couple of decades world technology changed in a way that raised the relative demand for skilled labor. The net impact on employment depends on the size of the two effects, H-O argument and technological one.

Several studies that measure the impact of trade reform on employment find almost no impact or small effects on employment. A possible explanation of the absence of the impact of trade policies on employment is aggregation of employment. This aggregation can mask the effects. In this paper we disaggregate labor into skilled and unskilled categories to analyse the effects of trade policies on different skills. Another possible reason for the lack of an employment response is that labor regulations, particularly in developing countries, inhibit the reallocation of labor (Currie and Harrison 1997). In this paper, we analyse and we introduce this phenomena.

In sum, there is considerable disagreement among analysts on the impact of recent trade reforms on labour. Our contribution to these debates in this paper is essentially an empirical issue. The analysis of a Tunisian firms data may be viewed as an attempt to apprehend how employment in Tunisia, a developing country, adjusted to the trade reforms. Using a micro-level detail on individual firms, we are able to trace the relationship between changes in trade policies and manufacturing employment at the firm level and by skill. Although trade reforms are generally implemented at the sector level, their effects may vary significantly across firm characteristics such as ownership (public vs. private) and degree of export orientation. We can then measure the effects of trade policy on employment for different types of firms. We also try to associate changes in employment directly with measure of change in trade protection, rather than link them to changes in imports and exports which is more common.

By using firm-level data we are also able to directly apply a model derived from the firm’s labor demand decision and to control for unobserved, constant firm-level determinants of labor demand using firm specific effects models. Introduction of technological change, labor adjustment and export orientation phenomena in the model plays an important role and have an impact on the response of employment to trade reform.
The rest of the paper is organized as follows. Section 2 presents a review of trade reform in Tunisia. Section 3 presents a discussion of necessary background about the impact of trade on employment. Section 4 lays down the main model to be used as framework for the empirical analysis. Section 5 presents the data and some basic descriptive statistics with some indications about the estimation method. Section 6 shows and discusses the main econometric results. Finally, section 7 concludes.

2. Trade liberalization in Tunisia

Since 1986, numerous measures have been taken to further liberalise the trade: the structural adjustment plan (1986), adherence to the GATT (1989), adherence to the OMC (1994) and the signature of a free-trade agreement with the European Union (1995). The Tunisian trade liberalization program can be divided into three periods (Cherkaoui and Naini 2002): The pre-structural adjustment program (SAP) adopted in 1986, during the SAP period (1987-94) and after 1995. Before 1986, over 94% of imports were subject to licensing, and tariff rates averaged 41 percent. In 1987, import licensing was gradually decreased and by 1991 only 30 percent of imports was subject to a license. The average import duties declined from 41 percent to 33 percent in 1987 and to 29 percent in 1990. The highest duty rate was reduced from 200 percent to 43 percent. There was a continuation of the removal of licensing requirements in 1992 and 1994. Since 1995 trade policy has been dominated by the free trade association agreement with the European Union. The agreement implies a removal of tariffs on industrial imports from Europe over a twelve-year period. This removal started in 1996.

The scope and speed of this trade liberalization episode is apparent from table1. The mean effective rate of protection1 fell from 555 in 1985 to 80 in 1991 for the IAA sector, from 203 in 1985 to 58 in 1991 in the ITHC sector and from 203 in 1985 to 49 in 1991 in the ICH sector. Disaggregated by industries, the percentage declines in effective rates of protection, particularly between 1986 and 1990, are impressive in all industries.

<Insert table 1 here>

In Summary, during the initial period of trade liberalization (1986-90), the degree of protection was greatly lowered. However, during the second period (1991-95) the nominal and the effective rates of protection increased except for some products. This increase is explained by the consequences of the Uruguay Round that transformed non-tariff protection into their tariff equivalent.

We have to note that liberalization program remains relatively timid over this period and concerns particularly equipment and inputs. The government has adopted a more active liberalization policy after 1995, but there is no plant-level data covering this period in Tunisia. However, our sample period covers an important phase of Tunisian trade reform (1987-1994), relatively to the protectionist period before 1986. The cross section dimension of our data covers firms belonging to different activities which are differently protected. This suggest that if trade has a significant effect on employment, it should be apparent in this data characterized by the two dimensions: temporal and individual.

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1 The effective rate of protection is defined as the proportional increase in value added resulting from the imposition of protective measures. It measures the percentage by which value added can increase over the free-trade level as a consequence of a tariff structure. The effective rate of protection captures protection of intermediate and final goods. It also captures tariff or non-tariff protective measures. A negative rate implies that input industries are particularly favoured. This negative rates indicate higher tariffs on input imports than on final goods.
The changes in the level of manufacturing employment by sector in Tunisia over the period 1971-1996 are shown in graph 1. We can identify a phase of rapid growth after 1987 which is accelerated after 1992 especially for the textile and industries diverses. We can also identify the dominant role of the textile sector in terms of job creation.

3. Trade liberalization and labour demand by skills: Some background

Let us consider the predictions of the H-O model and Stolper-Samuelson theorem in a simplified world that has two sectors, two factors of production (skilled and unskilled labor), and consists of a developed and a developing country. The developing country is assumed to be relatively unskilled labor abundant. When the developing country reduces trade barriers on the imported product, the Stolper-Samuelson theorem predicts that the decline in the price in the import-competing sector will hurt the factor of production used relatively intensively in the production of the imported good (skilled labor in developing countries) and benefit the factor of production used intensively in the export sector (unskilled labor in developing countries).

Edwards (1988), used a three-goods model (importables, exportables, and nontradables) to analyze labor-market adjustment to changes in the terms of trade and import tariffs for a small, open economy. The analysis looked at both long-run and short-run and assumed alternative assumptions regarding wage flexibility. The effects of the fall in the relative price of importables following liberalization in this type of model are in line with those predicted by the Stolper-Samuelson theorem; where exportables are relatively unskilled labour-intensive tariff reduction increases demand for the economy’s abundant factor. The within-tradeables shift in production and employment is towards exportables and away from importables, given the rise in the relative price of exportables. These changes entail an increase in the demand for unskilled labor in the unskilled labor abundant country. In developing countries, where unskilled labor is abundant and skilled labor is scarce, trade tends to raise both the demand for unskilled labor and the unskilled wages relative to the skilled wages.

However, this basic insight of the H-O model that trade should benefit a country’s abundant factor is quite compelling. More recent episodes of trade liberalization appear not to have been associated with large improvements in prospects for the typical worker (Hasan 2001), (Pavnick and al 2003). It is hard to avoid the conclusion that there is a genuine conflict of evidence. There are various factors that may explain the apparent divergence between the expectations of liberalization advocates and the recent evidence (Wood 1997).

A possible explanation is that over the past couple of decades world technology changed in a way that raised the relative demand for skilled labor. Technological change has been skill biased. Increased openness in a developing country affects the skill structure of labor demand by changing the production technology available through increased imports of advanced capital goods or through opportunities for exporters to learn from foreign buyers and be exposed to foreign markets. The net impact depends on the size of the two effects, H-O argument and technological one, and on the difference between domestic and world technology.
Another possible explanation is that realizing the gains from trade as expected by H-O model requires that factors are mobile and reallocate from import competing sectors to exporting sectors. Then labor market regulations can explain the sluggish labor market response to trade reforms in some countries, organized labor is usually viewed as an obstacle to labor market adjustment. In fact, hiring and firing laws may affect labor mobility. Legislations which make it difficult for firms to lay off workers are likely to impinge on firm’s ability to reallocate resources to new lines of production (Hasan 2001). Regulations and barriers to labor market mobility are likely to impede adjustment and dilute the benefits of trade reform for workers as a whole. Then labor markets were unaffected and firms adjusted to greater competition through other changes as reductions in profit margins (Currie, Harrison, 1997).

4. Model

This section outlines a simple model of employment determination which incorporates the effects of trade taking into account the effects of technological changes and the delay of adjustment of labor.

We begin by assuming that a firm-specific production function can be described by a Cobb-Douglas form as

\[ y_t = A_t^{\alpha} K_t^{\alpha} L_t^{\beta} \]  

where \( y_t \) indicates the output, \( K_t \) and \( L_t \) are capital and labor inputs, respectively. Capital stock is supposed to be fixed. \( \alpha \) and \( \beta \) are parameters to be estimated representing factor share coefficients. \( \gamma_t \) allows for factors affecting and changing the efficiency of the production process (Milner and Wright 1998). The factors considered here are related to trade liberalization. These factors vary over time and across firms (of the same sectors) in the following manner:

\[ A_t = \exp \left( \sum_t \gamma_t D_t \right) tpe^{\delta_t} \]  

where \( tpe \) is the effective protection rate. \( D_t \) is a dummy variable having a value of one for the \( t^{th} \) time period and zero otherwise and where \( \gamma_t \) are parameters to be estimated. The dummy variable \( D_t \) is introduced to model pure technology change according to the general index (GI) approach (Baltagi and Griffin 1988). This has the advantage of not imposing any structure on the behaviour of technical change. This time dummy model allows for the time effects to switch from positive to negative and back to positive effects. The change in \( \gamma_t \) between periods is a measure of the rate of technical change. This can be written as:

\[ TC_{t,t+1} = \gamma_{t+1} - \gamma_t \]  

The hypothesis of no technical change implies that \( \gamma_t = \text{constant} \) for all \( t \) in the model (2).

A firm’s derived demand for labour would therefore depend on output, stock of capital and the wage rate (\( w \)), together with the effective protection rate and time dummies.
However, the assumption of homogeneous workers in a firm can be considered as a strong hypothesis since it is likely that firms employ workers of different skills. In particular, firms most often employ both skilled and unskilled workers. As long as data about different categories of workers are available, one can estimate disaggregated labor demand models (Bresson, Kramarz et Sevestre 1992). This will permit us to analyze the effect of trade variables on demand for different categories of labor.

Consider that the firms’ production technology can be written as

$$y_{it} = f(K_{it}, L_{it}^1, L_{it}^2, A_{it})$$

(4)

$L_{it}^1$ the level of employment of skilled workers, $L_{it}^2$ the level of employment of unskilled workers.

We assume that, at first, firms determine an expected production and then minimize costs under the constraint of their expected level of production. Then the expression of the desired levels of employment for category $j$ $L_{it}^j, j = 1, 2$ in terms of their determinants (capital, production level...) can be derived from the solution of the firm optimisation program. In our context they depend on the production level, on the capital stock $K$, on the relative wages $\left(\frac{w_{it}^1}{w_{it}^2}\right)$ for the two workers categories considered together with the trade variables and the time trend (or dummies) which account for the technical progress. Since the wages by skill are not available in our data, the relative wage will be considered as fixed over time and vary only over firms, so that in estimations its variation will be captured by specific effects $\alpha_i$. We rely on the firm effects and on the time effects (time dummies) to absorb the effect of relative wages over the period and the firms.

The labor demand function for the category $j$ can be written as

$$L_{it}^j = g(y_{it}, K_{it}, tpe_{it}, D_t, \alpha_i)$$

(5)

However, to take into account the fact that when firms face a change in their environment, particularly trade reforms, they do not necessarily adjust immediately their level of employment to the new business conditions due to the existence of adjustment costs, namely hiring and firing costs, we use a dynamic adjustment process which can be represented as

$$L_{it}^j - L_{it-1}^j = \lambda^j (L_{it}^{j*} - L_{it-1}^{j*})$$

(6)

This would allow us to examine whether a firm’s response to trade shocks is related to the speed with which it adjusts to changes in desired employment levels. We suppose that the speed of adjustment depends on the skill level $j$, the dynamics of adjustment among labor inputs are different. One would expect hiring costs to be larger the higher the skill of workers, since training costs are expected to be lower for unskilled labor. Furthermore, since severance pay depends on the worker’s earnings and they depend on his skill, firing costs will increase with worker’s skill (Borrego, 1998).
For analytical convenience and computational easiness, adjustment costs were assumed to be symmetric and quadratic to derive explicit partial adjustment models of labor demand (Bresson and all, 1992).

Then, the labor demand function for category \( j \) can be rewritten as a reduced form equation for estimation:

\[
\ln L_{it} = (1-\lambda_j) \ln L_{it-1} + \lambda_j \theta_1 \ln y_{it} + \lambda_j \theta_2 \ln K_{it} + \lambda_j \theta_3 tpe_{it} + \lambda_j \theta_4 t + \alpha_i + v_{it} \\
\]

(7)

Coefficients are specific to the employment category \( j \). \( \alpha \) is the firm’s specific effect. \( v_{it} \) is the classical error term.

5. Data and estimation method

5.1. Data

The data used in this study are taken from the national annual survey report on firms (NASRF) carried out by the Tunisian National Institute of Statistics (TNIS). The data covers nearly all firms for different sectors (initially 5000) over the period 1983-1994. Although the data is collected by interviews, the Tunisian NASRF still suffers from a non-response mean rate of 57.5% for the period 1983-1988. Unfortunately, for the period 1989-1994, the TNIS does not report any information concerning both the non-response rate of firms and the reasons of non-response.

In the first stage, the data set has been “cleaned” from observations which could be seen as erroneous or which were clearly outliers. We have taken out firms observed less than 5 periods, this is an unavoidable consequence of the dynamic nature of the model and panel data techniques used. In the estimation of a dynamic function, we also required that all sample firms be observed consecutively. Thereby, our empirical analysis is based on an unbalanced panel consisting of a sample of 660 firms from the IAA, ICH and ITHC sectors (see table 3) with between 5 and 12 annual and continuous observations over the period 1983-1994 (see table 2). This sample is the only plant-level data available in Tunisia.

The data set includes: value added (∆y), capital stock (K) evaluated at historical values, labour (number of employees L), a decomposition of labour into skilled (L₁) and unskilled labour (L₂), and the total expenditure on personnel all categories is included. The activities of unskilled workers include machine operation, production supervision, repair, maintenance and cleaning; those of skilled workers include management, administration, and general office tasks. The number of employees is adjusted for whether it is part or fulltime equivalent employment. Labour costs for skilled and unskilled employees are combined, making it difficult to distinguish between the wages of the two types of workers. An average wage was calculated by dividing the total labour bill by the total number of employees. This wages

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\(^2\) Two years are lost in constructing lags and taking first differences, so that the estimation covers the period 1985-1994.
measure reflects both changes in worker remuneration and changes in the composition of the labour force.

The firm’s activity is described by a two-digit Tunisian nomenclature of economic activities. An aggregation to one-digit codes leads to the 6 industrial sectors.

As shown in table 4, our sample represents important percentages relatively to industrial employment.

<Insert table 4 here>

This table shows that our sample covers 27.5% of industrial employment and is very representative of the IME and ICH activities. The last two columns show that the distribution of employment across sectors in our sample and in the industrial data are comparable.

Since we are dealing with a pooled sample of individual firm data, the issue of firm heterogeneity is an important one. In our sample heterogeneity can arise from the fact that firms in different sectors of the industry can be expected to operate under different technologies which leads to differences in labour demand functions. This will be assumed to be a source of industry-specific heterogeneity, although in practice industries cannot be defined so finely that firm-specific differences in technology within a particular branch are eliminated.

<Insert table 5 here>

Table 5 provides an overview of the firms in our data set. The first column shows the mean characteristics of all firms in the sample, while columns two to six illustrate the difference between various groups of firms. This table shows that private firms are much larger than publicly owned firms in our sample and have a higher share of skilled workers. In addition, private industrial firms paid higher wages. This confirms the fact that public sector employees are underpaid. The last three columns break out firms in the three industry sectors considered in this study. Export-oriented firms belonging to the ITHC tend to be smaller, to have a smaller share of skilled workers and to have lower wages than other firms belonging to IAA and ICH industries. This is in conformity with the reality of the ITHC sector which is labor-intensive, employing an unskilled working population. Small firms and family owned firms dominate the Tunisian textile industry. ITHC is also dominated by firms that are totally oriented towards exportation, which specialize in subcontracting for foreign brands and platforms. Firms in ICH industries tend to be the larger ones, to have the highest share of skilled workers and to have the highest wages.

<Insert table 6 here>

Table 6 shows the ratio of skilled to unskilled employment for all firms. Between 1983 and 1993 the ratio of skilled to unskilled employment increased from 0.14 to 0.24. This ratio has doubled in the IAA and ICH sectors between 1983 and 1993.

<Insert table 7 here>
Table 7 shows relative employment by one digit industry for all firms in 1983 and 1993. Two industries experienced a significant increase in the relative employment of skilled labor (IAA, ICH), while one industry (ITHC) experienced a decline. The change in composition towards less use of unskilled workers relatively to skilled ones is fairly visible for the IAA and ICH sectors. One possible explanation for the rise in the relative demand for skilled labour is the skill-biased technical change which is accelerated by trade liberalization. In fact, trade is the vehicle through which new technologies enter most developing countries. This is because most innovations occur abroad and are imported in the form of machinery and equipment. The relaxation of trade barriers reduces the price of importing technology from abroad and could lead to surges in foreign direct investment and exports. If foreign firms and exporters demand more skilled workers, due to more advanced technology or differing product mixes, then this could explain a shift towards skilled employees (Harrison 1995). Trade liberalization permits the acceleration of the imported physical capital stock to GDP; the attendant capital-skill complementarities and bundled technology would then raise the relative demand for skilled workers. This explanation is also compatible with a greater degree of indirect skill inputs for exports required for marketing and distribution (OCDE 1996).

Our plant-level data were combined with measures on the effective rate of protection (tpe) calculated by the Institut d’Economie Quantitative (IEQ) at the 2-digit sector level and also at one digit level. Formally the effective rate of protection is given by the proportional increase in value added resulting from the imposition of protective measures. Thus the effective rate of protection is increased if the value added in the considered activity can be raised as a consequence of the imposition of any tariff or non-tariff protective measures. In principle, effective protection figures, which is a direct measure of trade policy, should summarize all of the product market forces that drive a wedge between domestic and world prices (Tybout and Westbrook 1995). The tpe measure combines information on tariffs with non-tariff barriers.

However, it seems worthwhile to also consider alternative measures of exposure to international competition: import licence coverage, official tariff rates, import penetration, but these measures are not available. We have already discuss the large decrease in tpe during the first observed period (84-90) and the somewhat stabilisation between 1991-94.

Our sample period covers an important phase of Tunisian trade reform (1987-1994), relatively to the protectionist period before 1986. The cross section dimension of our data covers firms belonging to different activities which are differently protected. This suggest that if trade has a significant effect on employment, it should be apparent in this data characterized by the two dimensions: temporal and individual.

However, we have to note that liberalization program remains relatively timid over this period and concerns particularly equipment and inputs and not final goods. This is mainly due to the government’s preoccupation with maintaining social stability and preparing companies for competition. The government has adopted a more active liberalization policy after 1995, but our plant-level data don’t cover this period.

5.2. Estimation method
We will estimate the dynamic model specified in equations (7) by GMM as suggested by Blundell and Bond (1998)\(^3\), without assuming any distribution for the error terms, taking into

\(^3\) See appendix for more details on this estimation method
consideration the dynamic form and the presence of variables that are invariants over time. Estimation of the dynamic error component model is considered using an alternative to the standard first differenced GMM estimator of Arellano and Bond (1991). It is a system GMM estimator deduced from a system of equations in first differences and in levels. This estimator is defined under extra moment restrictions that are available under quite reasonable conditions relating to the properties of the initial condition process. Exploiting these extra moment restrictions offers efficiency gains and permits the identification of the effects of time invariant variables.

6. Results

The empirical results are based on the estimation of equations (7) described above. The dependent variable in equation (7) is annual skilled, unskilled or total labour. The independent variables include the output, the capital stock and the protection variable: the effective rate of protection. All variables are expressed in logarithms. We also include year effects to control for common aggregate shocks that are not otherwise captured by our specification. In addition, to allow for the possibility of slow employment adjustment, we consider specifications that include lagged employment among the right-hand side variables. Introducing output among the list of explanatory variables in the employment equations, as is done in the regression equations 7, gives us a way of assessing the impact of openness after controlling for state of economic activity.

All regressions include year indicators. Note that it is crucial to control for unobserved year-specific variables that could influence employment concurrently with tariffs. Without controlling for year effects (macroeconomic shocks as exchange rate devaluation), one would falsely conclude that there is (or there is not) a relation between tariffs and employment.

Table 8 reports the estimation results of the dynamic employment function defined by equations (7) and estimated by the system GMM method. The first column reports the results for the total labour, the second reports the results for the unskilled labour demand and the third one reports the results for the skilled labour demand. The test of the hypothesis $\lambda = 1$ that there is no difference between target and actual labour use reject it at the 5 percent level of significance for the different categories of labour. This hypothesis is not appropriate for the data at hand.

<Insert table 8 here>

Output, capital and labour are considered as predetermined and correlated with firm-specific effects error. Consequently, the instruments used for equations in first differences are observations of capital and labour dated (t-2) and earlier in addition to output dated (t-2) and earlier. For the system GMM estimator, we add the observations on $(\Delta k, \Delta l, \Delta y)$ dated (t-1) and time dummies as instruments for the equations in levels.

The validity of the instrument set is checked using a sargan test. This is asymptotically distributed as chi-squared under the null. The instruments used in the first differenced GMM or in the system GMM are not rejected by the Sargan test of over-identifying. Tests of no

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4 For testing this hypothesis, a Student test of significativity of the coefficient associated to the lagged variable, that is $(1-\lambda)$, is sufficient.
serial correlation in the $v_t$ ($M_1$ and $M_2$)\(^5\) provide evidence to suggest that this assumption of serially uncorrelated errors is appropriate in the dynamic model as is shown in the different columns\(^6\). We note that the dynamic labour equations perform well in conventional statistical terms with no second order serial correlation and with a Sargan test for instrumental validity indicating that the instrument set and the residuals are not correlated. However, the test of no serial correlation of residuals is rejected in the static model. This indicates the presence of misspecification may be due to omission of the lagged dependent variable. The difference between the results for the static model and the dynamic are not negligible. The coefficients values estimates are different with more precision when costly adjustment of labour is accounted for in the model. The estimation of the system has made the identification of time-invariant variables effects possible in contrast to the first differenced estimation.

The coefficient estimates associated to the total labour shows that the coefficient on the lagged dependent variable is of 0.88 and strongly significant. The speed of adjustment is of 0.12, that is firms adjust only 12 percent of their deviations off the optimality in one year. This confirms the fact that labour takes time to reach its optimal level which is consistent with the existence of substantial employment protection. This is more pronounced for the skilled labour confirming the fact that adjustment costs are different for different skills. This also confirms the fact that to identify the impact of trade reform on labour we must take into account the adjustment delays of the labour. It suggests that the dynamics of the equations are important.

As regards the employment equations, we obtain fairly reasonable estimates. The coefficient on the output variable is positive and significant for the different categories of labour. Introducing the output variable among the explanatory variables in the employment equations, as is done in our regression equations, gives us a way of assessing the impact of openness on employment after controlling for state of economic activity. The coefficient on capital is not significant for the unskilled labour but significant and positive for the skilled labour demand. This result indicates that skilled labour and capital are complements.

With respect to the protection variable, our estimates are reasonable. We obtain a negative and significant coefficient on the variable that captures protection (tpe) for the different categories of labour. This suggests that a reduction in the protection rate is associated with an increase in labour demand. The coefficient on protection, -0.02, implies that a reduction in protection of 10 percentage points would lead to an increase in employment of 0.2 percent. The results suggest that unskilled employment is more responsive to changes in protection levels than that of skilled employment. The estimated elasticity of unskilled worker employment with respect to a change in protection levels is −0.05, whereas that for skilled employment is −0.029. It appears that firms adjusted to a contraction of the domestic market using other means of adjustment than cutting employment. This could reflect an improvement in productivity, efficiency and competitiveness resulting from more exposure and competition from abroad. Another explanation is the release of the input and capital constraint that allows the firm to use more (imported) capital equipment and other intermediate inputs at lower prices after liberalization. It is worth mentioning that the Tunisian industries, particularly the clothing industry, rely heavily on the importation of raw materials in order to meet production needs.

\(^5\) See the appendix for precision about these two tests $M_1$ and $M_2$
\(^6\) These tests statistics, distributed normally under the null of no serial correlation, are calculated and presented in the table 3.
In particular, increased exposure to trade could have increased the demand for skilled labor via skill-biased technological change. Wood (1995) argue that firms might adapt skill-biased technology in response to intensified competition from abroad. Lower prices of foreign machinery and technology provide an additional incentive for the firms to adapt new technology and then to increase their demand for skilled labor. Another explanation for the positive responses of employment is that the supply of labour increased dramatically in Tunisia as women and more educated people entered the labour market in the considered period. This allowed employment in the different sectors and for the different skills to be increased.

However, the results change somewhat when we consider different types of firms.

In tables 9 and 10, we report estimations for different types of firms. The results suggest that firm orientation and firm characteristics significantly affect both the magnitude and the sign of employment responses to trade policy. Columns 5 to 7 in table 9 show estimates for exporting firms (with mean export shares greater than 80%), the results suggest that decreases in protection were associated with significant increases in employment for the different categories. Columns 2 to 4 in table 9 show estimates for domestically oriented firms. The coefficient on protection is positive and significant suggesting that decreases in protection were associated with significant decreases in employment. It appears that domestically oriented firms adjusted to a contraction of the domestic market by cutting employment, while exporters used other means of adjustment.

Trade reforms may have increased exports by reducing tariffs on imported inputs. This suggest that export-oriented firms may have been net beneficiaries of the whole package of new policies. This can be also associated to the institutional reforms which made it attractive to produce for the export market.

In summary, the effects of openness on exporting manufacturing firms are positive rising employment as standard models of trade would predict for these unskilled labour-intensive firms in a developing country. This effects are negative for the domestically oriented firms leading to some reduction in employment.

It is interesting to note that, sometimes, trade variable has no effects on aggregate employment but has effects on skilled and unskilled labour separately. Hence, the effects of trade liberalization may not show up in global employment, this justifies the desegregation of employment into skilled and unskilled one.

The response of labour to output is more pronounced in the domestically- oriented firms than in the exporting ones.

The results obtained by distinguishing private from public firms (table 10) suggest that employment in the private and public firms react in a comparable manner to the measures of trade policy. For the majority of plants, the employment of skilled workers is not very responsive to changes in protection levels. The coefficients on effective protection rate are statistically insignificant, with point estimates close to zero. However, the effects of trade
reform are positive, rising the demand for unskilled labor in the private and in the public plants. The increase in employment due to a reduction in tariff protection is higher for private firms. Reductions in quota coverage and tariffs on imported inputs are associated with increases in unskilled labor demand perhaps reflecting increases in activity levels resulting from greater access to imported capital or other inputs in the private sector. However, the significant increase in the unskilled labor demand associated to decreases in protection level in the public sector is consistent with the idea that public employment acts as social safety net, absorbing employees in responses to an increase in labour supply.

<Insert table 10 here>

The coefficients on capital are positive and statistically significant for the skilled labor demand which is consistent with the hypothesis of complementarity between capital and skilled workers.

Total labor adjustment appear to be more sluggish in the public firms than in the private one. It is possible that public sector are more constrained in their ability to fire workers than private firms, which is consistent with the existence of substantial employment protection in the public sector. Public sector act usually as a social safety.

In order to test whether labor market adjustment in Tunisia is consistent with implications of Hecksher-Ohlin adjustments to trade reform, we also distinguish between industries. Industries are classified as importables or exportables on the basis of information about market orientation, the size of the import and export share and the policy regime. Textiles, clothing and leather (ITHC) are among the exportable sectors, while food (IAA) and chemical (ICH) industries are among importables sectors. The Stolper-Samuelson theorem predicts that the decline in the price in the import-competing sector will hurt the factor of production used relatively intensively in the production of the imported good (skilled labor) and benefit the factor of production used intensively in the export sector (unskilled labor).

So let us understand how adjustment occurred at the sector level to analyze whether certain sectors benefited more from the liberalization. In fact, much of the changes in employment following reforms could occur through within industries. Hence, the effects of trade liberalization may not show up in net industry employment.

<Insert table 11 here>

The effects of a fall in the relative price of importable following liberalization are in line with those predicted by the model of Edwards (1988). This model suggests that the impact of tariff reductions would serve to reduce the price of importables relative to that of exportables, and lead to a switch of production and employment in favour of exportables. Looking at the estimated responses for exportables (ITHC) (table 11), it may be seen that these correspond to those predicted theoretically. When exportables (ITHC here) are relatively unskilled-labour intensive, tariff reduction increases demand for the economy’s abundant factor and the within-tradeables shift in employment is towards exportables and away from importables (IAA and ICH), given the rise in the relative price of exportable. Trade reform should restore the comparative advantage to unskilled labour intensive goods (ITHC) and implies a reallocation of output toward unskilled labour intensive firms.
Finally, to investigate whether trade reforms were associated with the increase in the share of skilled workers observed in the IAA and ICH sectors (see tables 6 and 7), we regress the share of skilled workers against industry effective rate of protection and time indicators. The results indicate that the share of skilled workers is not directly related (in the different sectors: ITHC, ICH and IAA) to protection. These results are in conformity with the Stolper-Samuelson theorem and suggest that the increase in the share of skilled workers particularly observed in IAA and in ICH (between 1983 and 1993) cannot be attributed directly to liberalization. However, this is consistent with skill biased technological change. Skilled biased technological change could have been particularly induced by changes in foreign competition, so that trade liberalisation may have an indirect and not a direct effect on the rise of skill in IAA and ICH sectors.

7. Conclusion

This article presented micro-level evidence regarding the connection between trade policy and industrial sector employment.

This article is one of only a few studies that has examined this issue at the plant level and that are based on panel data and hence able to follow individual plants through time. It is the only study to address the effect of trade reform on employment by skills and using firms data in Tunisia. However, limited access to quality trade policy measures prevented us from fully exploiting the panel nature of the data.

The results suggest, souvent, that reductions in tariffs and non tariffs levels conducted in this first phase of liberalization in Tunisia are associated with moderate increase in firm labor demand. A 10 point reduction in TPE is associated with a 2 to 3% increase labour demand. When equations are estimated separately for unskilled and skilled labor, the paper finds that employment of the former is significantly more responsive to changes in protection levels than those of the latter.

The results also suggest that the impact of trade liberalization on labour demand depends on the characteristics of firms. In particular, the estimates obtained suggest that trade liberalization have beneficial effects on employment for exporting-firms. Conversely, trade liberalization have negative effects on employment for domestically oriented firms.

In sum, the trade liberalization have effects on labor market adjustment in Tunisia. It seems to have more effects on unskilled labour than on skilled labor, this justify the consideration of two skills. The exportable sectors react by increasing unskilled labor demand and the importable react by decreasing unskilled labor demand. This is some what consistent with the prediction of H-O model. The increase in demand of skilled labor in reaction to trade liberalization sometimes observed can be associated to skill biased technological change that was induced or accelerated by trade reforms. Skilled-biased technological change could have been partially induced by changes in foreign competition.
Table 1: Effective rates of protection in Tunisia in percentage terms

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>IAA</td>
<td>191</td>
<td>404</td>
<td>555</td>
<td>421</td>
<td>120</td>
<td>134</td>
<td>110</td>
<td>100</td>
<td>80</td>
<td>90</td>
<td>85</td>
<td>71</td>
</tr>
<tr>
<td>IMCCV</td>
<td>185</td>
<td>197</td>
<td>232</td>
<td>40</td>
<td>36</td>
<td>66</td>
<td>91</td>
<td>82</td>
<td>61</td>
<td>65</td>
<td>75</td>
<td>85</td>
</tr>
<tr>
<td>IME</td>
<td>67</td>
<td>92</td>
<td>104</td>
<td>88</td>
<td>73</td>
<td>63</td>
<td>98</td>
<td>101</td>
<td>55</td>
<td>59</td>
<td>65</td>
<td>64</td>
</tr>
<tr>
<td>ICH</td>
<td>161</td>
<td>92</td>
<td>100</td>
<td>88</td>
<td>67</td>
<td>62</td>
<td>70</td>
<td>78</td>
<td>49</td>
<td>50</td>
<td>60</td>
<td>65</td>
</tr>
<tr>
<td>ITHC</td>
<td>175</td>
<td>98</td>
<td>203</td>
<td>194</td>
<td>107</td>
<td>82</td>
<td>76</td>
<td>73</td>
<td>58</td>
<td>65</td>
<td>105</td>
<td>126</td>
</tr>
<tr>
<td>ID</td>
<td>150</td>
<td>122</td>
<td>134</td>
<td>101</td>
<td>88</td>
<td>74</td>
<td>78</td>
<td>80</td>
<td>54</td>
<td>65</td>
<td>90</td>
<td>102</td>
</tr>
<tr>
<td>Industries manufacturières</td>
<td>178</td>
<td>-</td>
<td>-</td>
<td>124</td>
<td>81</td>
<td>78</td>
<td>87</td>
<td>84</td>
<td>-</td>
<td>-</td>
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<td>-</td>
</tr>
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</table>

Graph 1: Employment trend for six industries

Table 2: Number of firms by periods

<table>
<thead>
<tr>
<th>Periods</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Firms</td>
<td>125</td>
<td>86</td>
<td>62</td>
<td>65</td>
<td>61</td>
<td>74</td>
<td>124</td>
<td>63</td>
</tr>
</tbody>
</table>

Table 3: Number of firms observed by industry
Table 4: Representativity of the sample

<table>
<thead>
<tr>
<th></th>
<th>Percentage of sectoral employment</th>
<th>Percentage of sample employment</th>
<th>Percentage of industrial employment</th>
</tr>
</thead>
<tbody>
<tr>
<td>IAA</td>
<td>31%</td>
<td>12.5%</td>
<td>11%</td>
</tr>
<tr>
<td>ICH</td>
<td>62%</td>
<td>10%</td>
<td>4.3%</td>
</tr>
<tr>
<td>ITHC</td>
<td>18.5%</td>
<td>33.7%</td>
<td>50%</td>
</tr>
<tr>
<td>total</td>
<td>27.5%</td>
<td>.....</td>
<td>.....</td>
</tr>
</tbody>
</table>

Table 5: Variables means

<table>
<thead>
<tr>
<th>Variables</th>
<th>All firms</th>
<th>Private firms</th>
<th>Public firms</th>
<th>ITHC</th>
<th>IAA</th>
<th>ICH</th>
</tr>
</thead>
<tbody>
<tr>
<td>Employment Skilled Unskilled</td>
<td>98.4 (203)</td>
<td>106 (214)</td>
<td>39.3 (66)</td>
<td>110 (157)</td>
<td>70.7 (166)</td>
<td>115 (366)</td>
</tr>
<tr>
<td>Ratio</td>
<td>14.7 (62)</td>
<td>16.1 (66)</td>
<td>4 (5.8)</td>
<td>11.7 (34)</td>
<td>12.8 (5.1)</td>
<td>29 (130)</td>
</tr>
<tr>
<td></td>
<td>83.7 (152)</td>
<td>90 (159)</td>
<td>36 (62)</td>
<td>98 (129)</td>
<td>57 (129)</td>
<td>85.6 (244)</td>
</tr>
<tr>
<td></td>
<td>0.175</td>
<td>0.178</td>
<td>0.11</td>
<td>0.119</td>
<td>0.224</td>
<td>0.338</td>
</tr>
<tr>
<td>Added value</td>
<td>716777 (2551455)</td>
<td>791621 (2705625)</td>
<td>157859 (323527)</td>
<td>525049 (1365644)</td>
<td>777504 (1794979)</td>
<td>1314791 (5580871)</td>
</tr>
<tr>
<td>Capital Stock</td>
<td>3866194 (26467588)</td>
<td>4318114 (28150818)</td>
<td>491392 (1103263)</td>
<td>1452586 (4333087)</td>
<td>4018946 (9502896)</td>
<td>12759036 (67628809)</td>
</tr>
<tr>
<td>Wage</td>
<td>2731 (1708)</td>
<td>2804 (1775)</td>
<td>2189 (909)</td>
<td>2163 (1091)</td>
<td>3307 (1960)</td>
<td>3618 (2171)</td>
</tr>
<tr>
<td>Exporting ratio</td>
<td>0.29 (0.39)</td>
<td>0.31 (0.39)</td>
<td>0.15 (0.31)</td>
<td>0.46 (0.41)</td>
<td>0.082 (0.22)</td>
<td>0.15 (0.29)</td>
</tr>
</tbody>
</table>
### Table 6: Ratio of skilled workers to unskilled workers (in means)

<table>
<thead>
<tr>
<th>year</th>
<th>3 industries</th>
<th>ITHC</th>
<th>ICH</th>
<th>IAA</th>
</tr>
</thead>
<tbody>
<tr>
<td>1983</td>
<td>0.145</td>
<td>0.137</td>
<td>0.25</td>
<td>0.14</td>
</tr>
<tr>
<td>1993</td>
<td>0.24</td>
<td>0.09</td>
<td>0.54</td>
<td>0.28</td>
</tr>
</tbody>
</table>

### Table 7: Ratio of skilled to total workers

<table>
<thead>
<tr>
<th>year</th>
<th>3 industries</th>
<th>ITHC</th>
<th>ICH</th>
<th>IAA</th>
</tr>
</thead>
<tbody>
<tr>
<td>1983</td>
<td>0.11</td>
<td>0.095</td>
<td>0.16</td>
<td>0.11</td>
</tr>
<tr>
<td>1993</td>
<td>0.13</td>
<td>0.098</td>
<td>0.2</td>
<td>0.14</td>
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</tbody>
</table>

### Table 8: Estimation results for all firms (660 firms)

<table>
<thead>
<tr>
<th>Coefficients</th>
<th>Total labour (L)</th>
<th>Unskilled labour (LU)</th>
<th>Skilled labour (LS)</th>
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</thead>
<tbody>
<tr>
<td>Ln L(-1)</td>
<td>0.88 (0.023) t=37</td>
<td>0.68 (0.019) t=34.3</td>
<td>0.55 (0.02) t=27.6</td>
</tr>
<tr>
<td>Ln y</td>
<td>0.115 (0.026) 4.39</td>
<td>0.25 (0.027) t=9.32</td>
<td>0.27 (0.027) t=10.3</td>
</tr>
<tr>
<td>Ln K</td>
<td>-0.001 (0.019) t=-0.099</td>
<td>-0.011 (0.026) t=-0.42</td>
<td>0.15 (0.024) t=6.44</td>
</tr>
<tr>
<td>Ln tpe</td>
<td>-0.020 (0.006) t= -3.11</td>
<td>-0.05 (0.008) t=-5.9</td>
<td>-0.029 (0.0079) t= -3.69</td>
</tr>
<tr>
<td>Year effects</td>
<td>yes</td>
<td>Yes</td>
<td>yes</td>
</tr>
<tr>
<td>M1: 1st order serial correlation</td>
<td>-12.057</td>
<td>-4.851</td>
<td>-9.152</td>
</tr>
<tr>
<td>M2: 2nd order serial correlation</td>
<td>-0.855</td>
<td>0.391</td>
<td>0.195</td>
</tr>
<tr>
<td>Sargan instrumental validity test (df)</td>
<td>131.01 (117)</td>
<td>137.6 (117)</td>
<td>173.3 (172)</td>
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</table>
Tableau 9: estimation results for exporting and domestically oriented firms

<table>
<thead>
<tr>
<th>Coefficients</th>
<th>Domestically oriented</th>
<th>Exporting firms</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>L total</td>
<td>L unskilled</td>
</tr>
<tr>
<td>Ln L(-1)</td>
<td>0.83 (0.018)</td>
<td>0.57 (0.013)</td>
</tr>
<tr>
<td></td>
<td>44.6</td>
<td>44.35</td>
</tr>
<tr>
<td>Ln y</td>
<td>0.21 (0.022)</td>
<td>0.48 (0.019)</td>
</tr>
<tr>
<td></td>
<td>9.79</td>
<td>24.8</td>
</tr>
<tr>
<td>Ln k</td>
<td>-0.11 (0.017)</td>
<td>-0.18 (0.016)</td>
</tr>
<tr>
<td></td>
<td>-6.52</td>
<td>-14.3</td>
</tr>
<tr>
<td>Ln tpe</td>
<td>0.0186 (0.010)</td>
<td>0.035 (0.009)</td>
</tr>
<tr>
<td></td>
<td>1.74</td>
<td>3.8</td>
</tr>
<tr>
<td>Year effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>M1: 1st order serial correlation</td>
<td>-5.403</td>
<td>-3.817</td>
</tr>
<tr>
<td>M2: 2nd order serial correlation</td>
<td>0.022</td>
<td>-0.357</td>
</tr>
<tr>
<td>Sargan instrumental validity test (df)</td>
<td>62.96 (62)</td>
<td>50.46 (62)</td>
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</table>

Tableau 10: Estimation results for private and public firms

<table>
<thead>
<tr>
<th>Coefficients</th>
<th>Private firms</th>
<th>Public firms</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>L total</td>
<td>L unskilled</td>
</tr>
<tr>
<td>Ln L(-1)</td>
<td>0.89 (0.022)</td>
<td>0.58 (0.021)</td>
</tr>
<tr>
<td></td>
<td>39.16</td>
<td>27.45</td>
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<tr>
<td>Ln y</td>
<td>0.105 (0.021)</td>
<td>0.21 (0.03)</td>
</tr>
<tr>
<td></td>
<td>4.86</td>
<td>7.05</td>
</tr>
<tr>
<td>Ln k</td>
<td>-0.016 (0.020)</td>
<td>0.091 (0.034)</td>
</tr>
<tr>
<td></td>
<td>-0.82</td>
<td>2.67</td>
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<tr>
<td>Ln tpe</td>
<td>-0.013 (0.0064)</td>
<td>-0.084 (0.013)</td>
</tr>
<tr>
<td></td>
<td>-2.12</td>
<td>-6.49</td>
</tr>
<tr>
<td>Year effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>M2: 2nd order serial correlation</td>
<td>0.022</td>
<td>-0.357</td>
</tr>
<tr>
<td>Sargan instrumental validity test (df)</td>
<td>62.96 (62)</td>
<td>50.46 (62)</td>
</tr>
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</table>
Table 11: Estimation results for the different sectors

<table>
<thead>
<tr>
<th>Coefficients</th>
<th>ITHC</th>
<th>IAA</th>
<th>ICH</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>L total</td>
<td>L unskilled</td>
<td>L total</td>
</tr>
<tr>
<td>Ln L(-1)</td>
<td>0.83 (0.043)</td>
<td>0.62 (0.049)</td>
<td>0.52 (0.037)</td>
</tr>
<tr>
<td></td>
<td>19.05</td>
<td>12.5</td>
<td>14.1</td>
</tr>
<tr>
<td>Ln y</td>
<td>0.147 (0.045)</td>
<td>0.30 (0.061)</td>
<td>0.43 (0.10)</td>
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<td>3.25</td>
<td>4.89</td>
<td>4.3</td>
</tr>
<tr>
<td>Ln k</td>
<td>-0.023 (0.032)</td>
<td>-0.024 (0.056)</td>
<td>0.033 (0.081)</td>
</tr>
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<td></td>
<td>-0.72</td>
<td>-0.44</td>
<td>0.40</td>
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<tr>
<td>Ln tpe</td>
<td>-0.014 (0.0098)</td>
<td>-0.034 (0.014)</td>
<td>0.031 (0.023)</td>
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<td></td>
<td>-1.47</td>
<td>-2.39</td>
<td>1.32</td>
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<td>Year effects</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>M2</td>
<td>0.147</td>
<td>-0.384</td>
<td>-1.227</td>
</tr>
<tr>
<td>Sargan</td>
<td>61.75 (62)</td>
<td>53.68 (62)</td>
<td>55.25 (62)</td>
</tr>
<tr>
<td>instrumental</td>
<td>validity test (df)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

(df)
References


Borrego (1998)


Appendix: Estimation methods

The labour demand function specified in equations (7) is characterised by the presence of the lagged dependent variable in addition to time-variant and time-invariant variables (activity) among the regressors. This is presented as follows

$$ y_i = \alpha + \lambda y_{i-1} + x_i' \beta + F_i' \rho + u_i \quad i=1,\ldots,N \text{ and } t=2,\ldots,T_i $$

where $x_i'$ is 1xk vector of explanatory variables, $F_i$ is a vector of time-invariant regressors, $(\beta, \rho)$ are the vectors of coefficients, $\alpha$ and $\lambda$ are scalars. $T_i$ is the number of ways the firm $i$ belongs. The error term is specified as follows

$$ u_i = \eta_i + v_i \quad \text{where} \quad \eta_i = \mu - \alpha_i \quad (\alpha = a_0 - \mu) $$

$v_{it}$ represents the effects, which can not be controlled by the firms and are assumed to be independently and identically distributed, $v_{it} \sim iid(0,\sigma_i^2)$, $\eta_i$ is a specific term assumed to be $iid(0,\sigma^2)$.

The model (1) can be rewritten as a standard error component model

$$ y_i = w_i' \theta + \eta_i + v_i \quad \text{Where} \quad w_i' = (1, y_{i-1}, x_i', F_i') $$

We suppose the familiar error components structure as it appears in Ahn and Schmidt (1995) where

i) For all $i$, $v_i$ is uncorrelated with $\eta_i$ for all $t$. $E(v_i \eta_i) = 0$ for $i=1,\ldots,N$ and $t=1,\ldots,T_i$.

ii) For all $i$, the $v_i$ are mutually uncorrelated. $E(v_i v_j) = 0$ for $i=1,\ldots,N$ and $t \neq s$.

In addition, there is the assumption concerning the initial conditions $y_{i0}$ (Ahn and Schmidt 1995,1997)

iii) For all $i$, $v_i$ is uncorrelated with $y_{i0}$ for all $t$.

Since $y_i$ is a function of $\eta_i$, $y_{i-1}$ is also a function of $\eta_i$. Therefore, $y_{i-1}$, a right-hand regressor in (1), is correlated with the error term. This renders the classical estimator biased and inconsistent (Baltagi 1995). The widely used estimator in this context is obtained by generalised method of moments (GMM) after first differencing to eliminate the correlated individual specific effects. Lagged levels of $y_i$ are used as instruments for equations in first differences (Arellano and Bond 1991). The first difference transformation wipes out the time-invariant variables, consequently the outcoming efficiency measure will be contaminated by
firm characteristics. More recently, Arellano et Bover (1995) and Blundell and Bond (1998) have shown that, under further and quite reasonable conditions relating to the properties of the initial condition process, there are additional moment conditions that are available for equations in levels. Exploiting these extra moment restrictions offers efficiency gains (Blundell and Bond 1998) and allows for controlling time invariant variables in estimating efficiency.

In what follows, we will review the first differenced GMM estimator and then describe the extended system GMM estimator.

1. Estimation in first differences

The assumptions (i), (ii) and (iii), imply the following moment conditions:

$$E(\Delta v_{it}, y_{i,t-s}) = 0 \quad s \geq 2 \text{ and } t=3 \ldots T_i$$  \hspace{1cm} (3)

$\Delta$ is the first difference operator.

These conditions imply that values of the dependent variable lagged two or more periods are valid instruments in the first differenced equations.

Conditions (3-3) may be expressed as: $E(Z_i' \Delta v_i) = 0$, where $\Delta v_i = (\Delta v_{i3}, \ldots, \Delta v_{iT_i})'$ is a 1x$(T_i-2)$ vector and $Z_i$ a $(T_i -2, m)$ matrix of instruments:

$$Z_i = \begin{bmatrix} y_{i1} & y_{i1} & \cdots & y_{i1} \\ y_{i2} & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ y_{iT_i} & y_{iT_i} & \cdots & 0 \end{bmatrix}$$  \hspace{1cm} (4)

In addition, we can exploit the exogeneity or the predetermineness assumptions about some or all of the explanatory variables (x_{it}) outside the lagged dependent variable (Arellano and Bond 1991). For example, if the x_{it} are predetermined, in the sense that $E(x_{it}v_s) \neq 0$ for $s < t$ and zero otherwise, then only $(x_{i1}', x_{i2}', \ldots, x_{is-1}')$ are valid instruments in the differenced equation for period s. If the x_{it} are strictly exogenous, i.e. $E(x_{it}v_s) = 0$ for all t,s, then all the x_{it} $(x_{i1}', x_{i2}', \ldots, x_{iT_i}')$ are valid instruments for all the equations. Clearly, x_{it} may include a combination of both predetermined and strictly exogenous variables.

\(^7\) The assumption of no serial correlation in the $v_{it}$ is essential for the validity of moments conditions (3-2). Thus, Arellano et Bond (1991) suggested tests for the absence of first-order (M1 test) and second-order serial correlation (M2 test) in the first-differenced residuals. If the disturbances $v_{it}$ are not serially correlated, there should be evidence of significant first order serial correlation in differenced residuals and no evidence of second order serial correlation in the differenced residuals.

\(^8\) We suppose here that the x_{it} are all correlated with $\eta_i$. 

However, the GMM estimator which exploits only the orthogonality conditions valid for the first differenced equations presents limits in the present study. First, it doesn’t allow the identification of time-invariant variables effects. Then, it doesn’t take into consideration the orthogonality conditions valid for equations in levels; hence it lacks in efficiency. This leads us to the estimation of a system of equations in differences and in levels.

2. A system estimator

We now turn to consider the case where the $x_{it}$ can be partitioned, following Hausman and Taylor (1981), into $(x_{1it}, x_{2it})$, and $x_{1it}$ is uncorrelated with $\eta_i$, additional moment restrictions exploiting this lack of correlation in the levels equations become available (Arellano and Bond 1991). For example, if $x_{1it}$ is predetermined, we can consider the following moment conditions

$$E(u_{it}x_{1it}) = 0 \quad \text{for } t=2, \ldots, T_i. \quad (5)$$

The time invariant variables $(F_i)$ can be partitioned in the same manner as $x_{it}$ into $(F_{1i}, F_{2i})$, and we can express additional moment conditions implied by these covariance restrictions

$$E(u_{it}F_{1i}) = 0 \quad \text{for } t=2, \ldots, T_i. \quad (6)$$

Then we have supplementary instruments valid in the levels equations. Arellano and Bover (1995) and Blundell and Bond (1998a) have discussed the use of additional linear moment conditions for the levels equations in the GMM framework. This allows the use of lagged differences of $y_{it}$ as instruments for equations in levels under further restrictions on the initial conditions process.

$$E(u_{it}y_{it-1}) = 0 \quad \text{for } t=3, \ldots, T_i. \quad (7)$$

The extended GMM estimator that uses these conditions, in addition to the usual conditions (3) offers efficiency gains (Blundell and Bond 1998a,b). To summarize, this imply a set of moment conditions relating to the equations in first differences and a set of moment conditions relating to the equations in levels, which need to be combined to obtain more efficient GMM estimator.

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9 Under the assumption that $F_{1i}$ is uncorrelated with $v_{it}$ for all $i$.

10 That is $E(u_{it}y_{it+2}) = 0$. An additional requirement is that $E(\Delta x, \eta_i) = 0$, this allows the use of lagged $\Delta x$ as instruments in levels equations (Blundell and Bond 1998a).

11 There are others moment conditions that are nonlinear in the parameters in the literature (Ahn and Schmidt 1995, 1997). Here, for computational ease, we exploit only linear conditions.
A system GMM estimator is based on a stacked system comprising all \((T_i-2)\) equations in first differences and the \((T_i-1)\) equations in levels. Define \(u_i^+\) the vector of errors in the system of \(((T_i-2)+(T_i-1))\) equations, 
\[ u_i^+ = (\Delta w_i', u_i')' \quad \text{with} \quad u_i = (u_{i2}, \ldots, u_{iT})'. \]
Let \(u^+ = (u_1^+, u_2^+, \ldots, u_N^+)' = y^+ - W^+ \theta \quad \text{where} \quad y^+ = ((\Delta v)', y')' \quad \text{(8)}\)

\(W^+\) is defined in the same manner as \(u^+, \quad W^+ = ((\Delta w)', w')' \quad \text{with} \quad w = (e, y_{-1}, X, F)\) is the explanatory variables matrix. \(\theta = (\alpha, \lambda, \beta', \rho')'\) is the coefficient vector. \(e\) is the vector unity.

The matrix of instruments for the system is defined as, \(Z^+ = (Z_1^+, Z_2^+, \ldots, Z_N^+)'\). For example, exploiting the restrictions (3) and (7) leads to the following matrix of instruments

\[
Z_i^+ = \begin{bmatrix}
Z_i & 0 & 0 & 0 & 0 & 0 & \cdots & 0 \\
0 & \Delta y_{i2} & \Delta x_{i2}' & 0 \\
\vdots & \Delta y_{i3} & \Delta x_{i3}' & 0 & \ddots & \vdots \\
0 & 0 & 0 & 0 & 0 & \cdots & \Delta y_{i(T-1)} & \Delta x_{i(T-1)}'
\end{bmatrix}
\]

which is of order \(((T_i-2)+(T_i-2), m)\); \(m\) is the number of instruments used. \(Z_i\) is the matrix defined in (4).

Let the instruments valid for first-differenced equations be \((Z_i^D)\) and those valid for equations in levels be \((Z_i^N)\), then \(Z_i^+\) can be rewritten as block diagonal matrix

\[
Z_i^+ = \begin{pmatrix}
Z_i^D \\ Z_i^N
\end{pmatrix}
\]

The orthogonality conditions are then summarized as

\[
E(Z^+ u^+) = 0 \quad \text{(9)}
\]

The generalised method of moments estimator based on these conditions minimises the quadratic distance \((u^+ Z^+ A_N Z^+ u^+)\) for some metric \(A_N\) and is defined as

\[
\hat{\theta}_{GMM} = (W^+ Z^+ A_N Z^+ W^+)^{-1}(W^+ Z^+ A_N Z^+ y^+) \quad \theta = (\alpha, \lambda, \beta', \rho')' \quad \text{(10)}
\]

Alternative choice for the weights \(A_N\) give rise to a set of GMM estimators, all of which are consistent for large \(N\) and finite \(T_i\), but which differ in their asymptotic efficiency. The optimal weights are given by

\[
A_N = (1/N \sum_{i=1}^{N} Z_i^+, \hat{u}_i^+, \hat{u}_i^+, Z_i^+)^{-1} \quad \text{(11)}
\]
Where $\hat{\epsilon}_i$ are residuals from an initial consistent estimator. The GMM estimator is then a two step estimator.

This linear GMM estimator obtained on a system is more efficient than the one obtained from the standard first-differenced model. It also permits the identification of time invariant variables.

The validity of orthogonality conditions is tested by the Sargan test based on the two-step GMM estimator (Arellano and Bond 1991)\textsuperscript{12}.

\[ S = (\hat{\epsilon}^*)' Z^* \left[ \sum_{i=1}^{N} Z_i^* (\hat{\epsilon}_i^*) (\hat{\epsilon}_i^*) Z_i^* \right]^{-1} Z^* (\hat{\epsilon}^*) \]

\textsuperscript{12} The statistic used, $S$, is distributed as a chi square with $(m-k-1)$ degree of freedom under the null hypothesis of the validity of instruments.