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Does the Hartz IV Reform have an Effect on Matching Efficiency in Germany? A Stochastic Frontier Approach*

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Abstract

In the course of a comprehensive labor market reform started in 2002 and finished through the implementation of the most radical measure Hartz IV in 2005, I exploit its impact on matching processes in Germany. I use disaggregated data for 178 local employment agencies to examine the effects of stocks and flows of vacancies and unemployed on the hiring rate as well as on the matching efficiency. Building on the work of Ibourk et al. (2004) and Fahr and Sunde (2006), I employ a stochastic frontier analysis. As a functional framework I choose the translog function to address the interactions of stocks and flows in generating new hires. Furthermore, the twofold structure of a stochastic frontier allows for a modeling of potential sources (e.g. Hartz IV) expected to induce an increased or decreased matching efficiency. My results suggest that Hartz IV exhibits a significantly positive impact on the hiring rate and the matching efficiency. Compared to 1998, on average matching efficiency experienced an increase in 2007.

JEL classification: C23, C24, J64, J68

Keywords: Labor Market Reform, Matching Models, Stochastic Frontier Analysis, Germany

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1 Introduction

Apart from the recent development of the European labor markets since the beginning of the financial crisis in 2007, Germany has had to deal with high unemployment rates along with a huge and persistent stock of long-term unemployed. Of all OECD countries in 2007, only France, Turkey, Poland, Crotia and Slovakia had to face higher unemployment rates than Germany, which had an average of 8.4%. Although the unemployment rate in Germany declined during 2007 and 2008, a long-term unemployment rate of 4.7% in 2007 and 3.8% in 2008 is still high compared to other OECD countries. In Gemany almost 50% of all unemployed are on average unemployed for longer than one year.[1]

In addition to the broad gap between the unemployment rates in West Germany and the federal states of the former German Democratic Republic, there are also considerable disparities across regions within both former East and West Germany.[2] To relieve the large disparities between regions and to promote employment, the German government subsequently implemented a series of "Hartz" laws.[3] These laws were part of a comprehensive reform program, which came into effect between 2003-2005, primarily applied to the labor market and generally known as the Agenda 2010.[4] The set of reform elements is aimed at improving the labor market services in terms of effectiveness and efficiency. To enhance the performance of the job placement process, the highly centralized institutional structure of the Federal Employment Agency was completely modernized. More specifically, it was turned into a decentralized organization with many job centers established by local employment agencies. These job centers are allowed to cooperate with private placement services.[5] Since 2003, every local employment agency has set up a Personal Service Agentur (PSA), that acts like a private agency.[6] The local employment agency delegates

[1]Only Poland and Slovakia exhibited higher long-term unemployment rates in 2007 and 2008. See *ec.europa.eu/eurostat* for comprehensive statistics on labor market indicators

[2]See OECD Employment Outlook 2008 for further details and figures.

[3]The laws are named after Peter Hartz, the chairman of the commission that set up the policy design of those laws.

[4]In January 2003 the first two "Hartz" laws (Hartz I, Hartz II), in 2004 Hartz III and in 2005 the fourth law (Hartz IV) came into effect.

[5]A job seeker who hasn't been placed successfully by a local employment agency after six months may choose a private placement service. If this private agency succeeds in placing the unemployed it receives a lump sump payment.

[6]See Jacobi and Kluve (2006) for an extensive description of the Hartz reforms and a literature overview of all

selected hard-to-place unemployed, such as long-term or older unemployed, to a PSA. Like a private placement agency, the PSA in turn receives a lump sum fee for each successfully placed unemployed. In case the unemployed cannot be placed, the PSA provides training measures. Since problem groups among the unemployed are the low skilled, old, long-term and foreign unemployed, Hartz IV, the most radical measure, primarily aims at encouraging the unemployed as well as improving their placement process. Through the creation of sanction schemes, especially concerning unemployment benefits, unemployed are more or less forced to increase their efforts in finding a job. Before Hartz IV, unemployed received unemployment benefits indefinitely regardless of whether they were actively engaged in job search or not. Nowadays, those unemployed who persistently refuse moderate[7] job offers, have to expect a reduction of their unemployment benefits after a certain period of time or a certain number of refusals.[8] Clearly, this last reform step - Hartz IV - places great emphasis on measures that promote a direct (re-)integration into the labor market as opposed to training measures, public job creation schemes and a restructuring of the federal employment agencies enacted by Hartz I, II and III.

Insofar, the question I will address in this paper is how matching efficiency has evolved over time and between regions in the course of the reform program. In particular, has Hartz IV contributed to an increased matching efficiency after its implementation in January 2005? Following Fahr and Sunde (2006), Ibourk et al. (2004) and Hynninen (2009), I employ a stochastic frontier function to model the matching process with both stocks and flows of vacancies and unemployed for Germany in order to evaluate the regions with the most efficient matching processes.

Furthermore, it has been proven in empirical studies (Coles and Smith (1998), Gregg and Petrongolo (2005), Coles and Petrongolo (2008)), that the stock of unemployed is more likely to match up with the inflow of newly registered jobs than with the job vacancy stock. Similarily, it is more probable that an individual, having recently become unemployed, gets matched with a job belonging to the vacancy stock.[9] To reflect these interactions and their impact on the matching

recent studies considering the evaluation of active labor market policies, especially the Hartz effects, in Germany.

[7]The defintion of moderate, acceptable or suitable work has been broadened. For instance, under very limited circumstances, the unemployed are obliged to move to different regions in order to take a job.

[8]Another purpose of the reform program was to increase the flexibility of the labor market e.g. by relaxing job protection and lowering social-security contributions for certain part-time jobs, namely "mini-jobs" and "midi-jobs".

[9]Coles and Smith (1998) describe a marketplace framework to analyze the matching probability of workers by

process, I select a flexible translog function as underlying framework for the stochastic frontier analysis. It rather appears as an adequate functional form to investigate whether new hirings are principally generated by the interactions of stocks and flows or simply by either stocks or flows of unemployed and vacancies. Recently, Fahr and Sunde (2009) conducted a non-stochastic frontier analysis using monthly data from March 2000 to December 2004 to estimate the extent to which stocks and flows of unemployed and vacancies affect the matching process in the course of Hartz I - Hartz III.[10]

Summing up, this paper represents the first approach to evaluate a change in the matching efficiency in Germany mainly after the implementation of Hartz IV by applying a stochastic translog frontier to monthly data of 178 local employment agencies from January 1998 to January 2008.

The paper proceeds as follows. Section 2 introduces several functional frameworks of a stochastic frontier and the specification of the inefficiency term. Section 3 provides a description of the regional data set used for my empirical analysis. The core results of the stochastic frontier estimation and the matching efficiencies are presented and disussed in section 4 which is followed by the conclusion in section 5.

2 The Model Framework

As the estimates of the regional matching efficiencies are of particular interest, a proper stochastic frontier function has to be set up. Commonly, the matching or unemployment outflow rate is modeled by means of a Cobb-Douglas function with the stocks or both the stocks and flows of unemployed and vacancies. However, the translog function offers anonther approach: It relates the stocks and flows of unemployed and vacancies, their quadratic terms and crossproducts to the number of matches. Hence, it appears as an appropriate functional form that allows to

duration classes in U.K. Job Centers depending on the stocks and flows of unemployed workers and vacancies. Their results suggest, that the longer a person remains unemployed the more probable a match with an incoming vacancy compared with a vacancy from the vacancy pool. In contrast, it is more likely that the unemployment inflow matches with the vacancy stock. The findings of Coles and Smith (1998) point out the importance to examine the stock-flow interaction as a driving factor in generating new matches.

[10]Fahr and Sunde (2009) estimate several fixed effects specifications of a Cobb-Douglas matching functions over 178 local employment agencies for several time intervals, but only consider data up to December 2004.

investigate whether new hirings are principally generated by the interactions of stocks and flows or by either stocks or flows of unemployed and vacancies. Some critique has been presented against the Cobb-Douglas specification by Yashiv (2000) and Warren (1996). The next section introduces the model framework composed of a stochastic frontier function and an inefficiency term. Several functional forms will be presented, followed by a precise specification of both frontier and inefficiency term for the estimation, forthcoming in section 4.

2.1 The Frontier Function

In principle, the matching process can be modeled as the number of matches M_{it} as a function of the stocks and flows (^{F}) of unemployed, U_{it}, U_{it}^F and vacancies, V_{it}, V_{it}^F in month t and region i:

$$M_{it} = f(U_{it}, V_{it}, U_{it}^F, V_{it}^F) TE_{it}. \tag{1}$$

Moreover, in case of the stochastic frontier, the number of hirings depends on an efficiency term TE_{it} allowed to vary over time and between regions. The inefficiency term enters the model as $\ln TE_{it} = -\vartheta_{it}$, where $\vartheta_{it} \geq 0$ is defined as a measure of *technical inefficiency* since $\vartheta_{it} = -\ln TE_{it} \approx 1 - TE_{it}$.[11] As frontier function $f(\cdot)$, I primarily assume a flexible translog function:[12]

$$\ln m_{it} = (\alpha_0 + \sum_k \alpha_k \ln x_{it,k} + 0.5 \sum_k \sum_l \beta_{kl} \ln x_{it,k} x_{it,l} + \epsilon_{it}) - \vartheta_{it}, \tag{2}$$

with $k = \{u, v, u^F, v^F\}$, thus $x_{it,u} = \frac{U_{it}}{L_{it}} = u_{it}$, $x_{it,v} = \frac{V_{it}}{L_{it}} = v_{it}$, $x_{it,u^F} = \frac{U_{it}^F}{L_{it}} = u_{it}^F$ and $x_{it,v^F} = \frac{V_{it}^F}{L_{it}} = v_{it}^F$.

[11] The advantage of a stochastic compared to a deterministic frontier is, that unusual effects are not necessarily considered as stochastic. In case of a deterministic frontier, imperfections, especially with respect to model specification and measurement errors, cause an increasing or decreasing efficiency over time. In terms of the model in equation (2), ϵ_{it} accounts for all the irregularities which do not coincide with a change in the efficiency. In a deterministic frontier the random error ϑ_{it} is missing. Consequently, all effects which are not measured by the explanatory variables are captured by the term ϵ_{it}. See Greene (2007) for an extensive survey on efficiency analysis using a stochastic frontier.

[12] See Berndt and Christensen (1973) for a derivation of the transcendental function and its application to the U.S. manufacturing sector.

m_{it} is defined as the rate of unemployment outflow to employment covered by social security. u_{it} and v_{it} enter the model as unemployment and vacancy rates at the beginning of month t. The inflow rates of unemployed and vacancies, denoted as u_{it}^F and v_{it}^F, capture all unemployed and vacant jobs which have been registered at the local employment agency (LEA) in region i during month t. All variables are adjusted by the size of the labor force L_{it} and thus reported as rates.[13] ϵ_{it} is white noise with $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$.

To find out whether the translog function is a more proper matching framework, I estimate three specifications to allow for a comparison among them. Hence, besides the translog function, I select the Cobb-Doulglas and the nonlinear CES function. The CES function imposes a constant elasticity of substitution σ among the input factors.[14] Since the CES function cannot be linearized analytically, Kmenta (1967) derives the two-input CES function as an approximation of a linearized Taylor series given a substitution parameter ρ close to zero and, accordingly, an elasticity of substitution σ with $\sigma = \frac{1}{1+\rho}$ near to unity. The nonlinear stochastic stock-stock CES production frontier is written as:

$$m_{it} = \psi[\delta u_{it}^{-\rho} + (1-\delta)v_{it}^{-\rho}]^{-\frac{\nu}{\rho}} \cdot TE_{it} \tag{3}$$

with ψ as an efficiency parameter, δ and $1-\delta$ as distributional parameters describing the share of the unemployment and vacancy rates on the hiring rate. ν is the resturns-to-scale parameter.[15] By means of the Taylor approximation, the nonlinear CES function corresponds to the following stochastic CES production frontier:

[13]Munich et al. (1998) argue that the variables have to be adjusted by the size of the labor force L_{it}. They demonstrate the impact of the spurious scale effect on estimation using data at the regional level. The estimation of a model without variables adjusted by the size of the regional labor force yields biased estimates in case of increasing or decreasing returns to scale. Only if the underlying matching function displays constant returns to scale or $Corr(L_{it}U_{it}) = Corr(L_{it}V_{it}) = Corr(L_{it}U_{it}^F) = Corr(L_{it}V_{it}^F) = 0$ are the estimates of an unadjusted model equivalent to those of an adjusted model.

[14]In the two factor case, meaning the stock-stock matching function approach, the elasticity of substition between vacancies and unemployed is assumed to be constant. In the stock-flow model (the four factor case) the elasticity of substitution σ between both stocks and flows of unemployed and vacancies remains constant.

[15]All parameters are strictly greater than zero except the substitution parameter ρ which has a lower bound -1.

$$\ln m_{it} = \ln\psi + \nu\delta\ln u_{it} + \nu(1-\delta)\ln v_{it} - 0.5\rho\nu\delta(1-\delta)[\ln u_{it} - \ln v_{it}]^2 + \epsilon_{it} - \vartheta_{it}. \quad (4)$$

The restricted approximation of the nonlinear CES function in equation (4) can be rewritten as an unrestricted version:

$$\ln m_{it} = \alpha_0 + \alpha_1\ln u_{it} + \alpha_2\ln v_{it} + \alpha_3(\ln u_{it} - \ln v_{it})^2 + \epsilon_{it} - \vartheta_{it}. \quad (5)$$

Finally, the parameters in equation (4) are derived by means of the unrestricted α-coefficients:

$$\begin{aligned} \psi &= exp(\alpha_0) \\ \nu &= \alpha_1 + \alpha_2 \\ \delta &= \frac{\alpha_1}{\nu} \\ (1-\delta) &= \frac{\alpha_2}{\nu} \\ \rho &= \frac{-2\alpha_3\nu}{\alpha_1\alpha_2}. \end{aligned} \quad (6)$$

The same transformation has to be applied to the four factor (stock-flow) stochastic CES production frontier.[16] Hence, the stock-flow approach of an approximated stochastic CES production

[16]The starting point of the approximation is the nonlinear stock-flow CES production function with $M_{it} = \psi[\delta_1 U_{it}^{-\rho} + \delta_2 V_{it}^{-\rho} + \delta_3 (U_{it}^F)^{-\rho} + (1-\delta_1-\delta_2-\delta_3)(V_{it}^F)^{-\rho}]^{-\frac{\nu}{\rho}} \cdot TE_{it}$. In addition to the traditional two-factor CES model, Chen and Lin (2009) develop a three factor CES stochastic production frontier model and apply it to panel data from 15 countries over the period 1993-2003.

frontier is given by:

$$
\begin{aligned}
\ln m_{it} = & \underbrace{\ln \psi}_{=\alpha_0} + \underbrace{\nu\delta_1}_{=\alpha_1} \ln u_{it} + \underbrace{\nu\delta_2}_{=\alpha_2} \ln v_{it} + \underbrace{\nu\delta_3}_{=\alpha_3} \ln u^F_{it} + \underbrace{\nu(1-\delta_1-\delta_2-\delta_3)}_{=\alpha_4} \ln v^F_{it} \\
& \underbrace{-0.5\rho\nu\delta_1\delta_2}_{=\alpha_5}[\ln u_{it} - \ln v_{it}]^2 \\
& \underbrace{-0.5\rho\nu\delta_1\delta_3}_{=\alpha_6}[\ln u_{it} - \ln u^F_{it}]^2 \\
& \underbrace{-0.5\rho\nu\delta_1(1-\delta_1-\delta_2-\delta_3)}_{=\alpha_7}[\ln u_{it} - \ln v^F_{it}]^2 \\
& \underbrace{-0.5\rho\nu\delta_2\delta_3}_{=\alpha_8}[\ln v_{it} - \ln u^F_{it}]^2 \\
& \underbrace{-0.5\rho\nu\delta_2(1-\delta_1-\delta_2-\delta_3)}_{=\alpha_9}[\ln v_{it} - \ln v^F_{it}]^2 \\
& \underbrace{-0.5\rho\nu\delta_3(1-\delta_1-\delta_2-\delta_3)}_{=\alpha_{10}}[\ln u^F_{it} - \ln v^F_{it}]^2 + \epsilon_{it} - \vartheta_{it}. \qquad (7)
\end{aligned}
$$

The α-coefficients of the unrestricted model, similar to equation (5) for the two-factor case, relate to the coefficients of the restricted stochastic approximation as follows:

$$
\begin{aligned}
\psi &= exp(\alpha_0) \\
\nu &= \alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 \\
\delta_1 &= \frac{\alpha_1}{\nu} \\
\delta_2 &= \frac{\alpha_2}{\nu} \\
\delta_3 &= \frac{\alpha_3}{\nu} \\
(1-\delta_1-\delta_2-\delta_3) &= \frac{\alpha_4}{\nu}. \qquad (8)
\end{aligned}
$$

The measures of substitutability or complementarity between stocks and flows of unemployed and vacancies are evaluated with ρ_j, $j = 1, ..., 6$ for the four-factor case. Given the relationships between the α-coefficients of the unrestricted and the parameters $\nu = \sum_1^4 \alpha_m$ with $m = 1, ..., 4$

and δ_n with $n = 1, ..., 4$[17] of the restricted model, the several ρ-values are

$$\begin{aligned}
\rho_1 &= \frac{-2\alpha_5\nu}{\alpha_1\alpha_2} \\
\rho_2 &= \frac{-2\alpha_6\nu}{\alpha_1\alpha_3} \\
\rho_3 &= \frac{-2\alpha_7\nu}{\alpha_1\alpha_4} \\
\rho_4 &= \frac{-2\alpha_8\nu}{\alpha_2\alpha_3} \\
\rho_5 &= \frac{-2\alpha_9\nu}{\alpha_2\alpha_4} \\
\rho_6 &= \frac{-2\alpha_{10}\nu}{\alpha_3\alpha_4}.
\end{aligned} \tag{9}$$

As the substitution parameter ρ becomes zero, the linearized stock-flow CES function in equation (7), collapses to a standard Cobb Douglas function[18]

$$\ln m_{it} = \underbrace{\ln\psi}_{=\alpha_0} + \underbrace{\nu\delta_1}_{=\alpha_1} \ln u_{it} + \underbrace{\nu\delta_2}_{=\alpha_2} \ln v_{it} + \underbrace{\nu\delta_3}_{=\alpha_3} \ln u_{it}^F + \underbrace{\nu(1-\delta_1-\delta_2-\delta_3)}_{=\alpha_4} \ln v_{it}^F + \epsilon_{it} - \vartheta_{it}. \tag{10}$$

The results of a model selection process in section 4.1 identify one of these functional forms in equations (2), (5) or (7) and (10) as the most appropriate function for the stochastic frontier.

Irrespective of the functional framework, a dummy *2005:01* and 11 monthly dummies to account for seasonal fluctuations are added alongside the CES, Cobb-Douglas and translog frontier for the estimation in section 4. The dummy *2005:01*, which takes the value 1 in January 2005, is supposed to capture the structural break occuring in the data at that point.[19]

Fahr and Sunde (2006) estimate occupational and regional matching efficiencies for 117 local employment agencies in Western Germany by applying a stochastic production frontier to yearly

[17] δ_4 is computed as $\delta_4 = 1 - \delta_1 - \delta_2 - \delta_3$

[18] Like the linearized two-factor CES function, the four-factor CES function in equation (7) is constituted by two parts: the first part simply represents a standard Cobb-Douglas function and the second part is an adjustment driven by the substitution parameter ρ. As ρ converges to zero, the adjustment disappears and the CES function approaches the Cobb-Douglas function.

[19] The structural data break was caused by a change in the definition of the unemployment status. More specifically, all social contribution recipients, who did not count as unemployed before January 2005 had to register as unemployed. Clearly, this was followed by a sharp increase in the number of unemployed, solely due to statistical reasons.

data from 1980-1997. They use a Cobb Douglas framework as a frontier function with the stocks of unemployed and vacancies. The inefficiency term is specified in dependence on whether the analysis is conducted for occupations or for regions. Hynninen (2009) investigates the composition of the job-seeker stock in labor market matching through a stochastic production frontier applied to monthly data from 145 local labour offices in Finland between 1995 and 2004. Hynninen (2009) estimates a conventional random and fixed-effects model besides the three different stochastic frontier models. The matching process is supposed to follow the conditions and restrictions of a Cobb-Douglas production function. A study by Ibourk et al. (2004) analyzes the change in matching efficiencies for 22 French regions from March 1990 till February 1994. Unlike other studies, Ibourk et al. (2004) use a translog function for the stochastic frontier.

2.2 The Inefficiency Term

As mentioned in section 2.1, the efficiency term TE_{it}, with $-\ln TE_{it} = \vartheta_{it}$, represents the second part of a stochastic efficiency frontier. Recently, Battese and Coelli (1995) have proposed a widely adopted distributional assumption of ϑ_{it} to allow for variations of both over time and across regions.[20] More precisely, they model the **in**efficiency ϑ_{it} as a function of observed characteristics, expressed by a $(1 \times K)$ vector z_{it}, which are likely to explain the efficiency of the matching technology. Hence, the ϑ_{it}-errors are denoted by:

$$\ln \vartheta_{it} = z_{it}\zeta + \omega_{it}, \tag{11}$$

where ζ is a $(K \times 1)$ vector of unknown parameters to be estimated. Following Battese and Coelli (1995), I define ω_{it} with $\omega_{it} \geq -z_{it}\zeta$ as an unobservable *iid* distributed random variable, obtained by truncation of the normal distribution with mean zero and an unknown variance σ_ω^2 and with a truncation point at $-z_{it}\zeta$. Accordingly, ϑ_{it} is a non-negative truncation of the normal distribution with $N(z_{it}\zeta, \sigma_\omega^2)$. The technical efficiencies, conditional on the estimated coefficients of the unemployment and vacancy rates for stocks and flows as well as the hirings rate, are then computed as follows:[21]

[20] See Aigner et al. (1977) for alternative distributional assumptions of the inefficiency term.

[21] The parameter estimates of the stochastic frontier and the inefficency term are achieved simultaneously by

$$\hat{\vartheta_{it}} = exp(-(z_{it}\hat{\zeta} + \hat{\omega}_{it})). \quad (12)$$

The z_{it}-vector in (13) is a group of variables describing the structure of the unemployed workforce, controls for the Hartz IV reform, business cycle and social and region-specific fluctuations of an economy

$$\begin{aligned} z_{it} =&(young_{it}, old_{it}, long_{it}, fem_{it}, non_{it}, \\ & ifo_t, HartzIV_t, PopDens_{it}, PopDens2_{it}, east_i, trend_t). \end{aligned} \quad (13)$$

In detail, I include the unemployment rate of unemployed workers equal to or younger than the age of 25 (*young*), of those equal or older than 55 years (*old*), the long term (*long*), the female (fem) and the foreign unemployment rate (*non*) as explanatories for inefficiencies.[22] The variables are likely to reflect the search intensity of these key problem groups. Although equally important and in the same space of arguments, the model does not, however, provide variables accounting fo the educational attainment of the unemployed. Commonly, the share of high and low skilled unemployed is included implying higher employment probabilties of those possessing an university degree compared to individuals who neither finished high school nor obtained a vocational degree. However, due to inconsistencies in statistical recording of data on education levels of registered unemployed since 2005, I estimate the stochastic frontier model without consideration of skill attainment.[23]

Changes due to business cycle fluctuations, such as an intensified search behavior on the worker side as well as on the firm side, are comprised by the ifo index (ifo_t) - a non-district specific measure of the monthly business expectations of German entrepreneurs.[24]

maximizing the log-likelihood of the model. See Battese and Coelli (1995) for a derivation of the likelihood function.

[22]All person more than 12 months without employment are classified as long-term unemployed.

[23]Unemployed enter the statistics not according to their obtained vocational degree but according to their career aspiration. For instance, a skilled baker who is not able to continue the profession, registers as unemployed by indicating an alternative job he or she wished to apply for in the future. Consequently, it is not recommended to draw conclusions regarding the qualification of the particular unemployed. Since January 2009 a plausible evaluation of the unemployed according to their recently obtained vocational degree is possible.

[24]There are three different indices for the business cycle provided by the ifo-Institute in Munich, Germany. In following Fahr and Sunde (2009) I use the index R3 which reflects the business expectations.

Since I postulate that Hartz IV, the last step of the Hartz reforms, induces a strong effect on matching efficiency, I include an "exponential" dummy ($HartzIV_t$). Opposed to a step dummy, switching from 0 to 1 in one period, this dummy variable exponentially increases from 0 up to 1 in 12 months according to a specific growth rate.[25] Even though Hartz IV came into effect in January 2005, agents on both sides, the local employment agencies (LEA) and the unemployed job seekers, have had to learn and adjust their placement and search intensity, respectively, according to the rules set by Hartz IV. Clearly, this justifies a dummy variable, which not immediately takes the value 1 in January 2005 when the law was implemented.

The frequency of how often contacts are established between unemployed workers and firms and how many times those contacts lead to an employment, is clearly a factor of how densely areas are populated. As a result, population density ($PopDens_{it}$) enters the inefficiency term and is meant to control for effects caused by the density of economic activities. For unemployed workers in sparely populated rural areas, the job matching is likely to be more difficult than for unemployed in densely populated urban areas.[26] However, this positive impact on the hiring rate is supposed to become negative as the area gets too densely populated. The advantage of a more developed social network and an easier access to information/media is then offset by an increased competition for jobs among the unemployed workers. To consider this turning point, a quadratic term of population density ($PopDens2_{it}$) is added to the z_{it}-vector. The dummy variable $East_i$ takes the value 1 if the LEA is located in the territory of the former German Democratic Republic. Since with Hartz I, II and III the reorganization of the Federal Employment Agency and its related LEAs has already been started, this may have exhibited an effect on the placement productivity of the LEAs. Accordingly, I include a time trend to reflect the adjusting behavior of the LEAs and other macroeconomic changes that occurred during the observation period.

In a simpler form, the inefficiency term ϑ_{it} is solely a function of time and not modeled itself by a set of explanatory variables, given by:

[25] For further details on the growth rate, please contact the author.

[26] Despite the substantial emigration from Eastern to Western Germany not all regions in East Germany lost a high share of their population, some even attracted people.

$$\vartheta_{it} = \eta_{it}\vartheta_i = exp(-\eta(t-T)\vartheta_i), \tag{14}$$

whereas the last period ($t = T$) contains the base level of inefficiency. If $\eta > 0, \eta = 0$ or $\eta < 0$, the inefficiency in region i increases, remains constant or decreases over time.

3 Data and Description

To estimate the stochastic frontier, I employ a highly disaggregated monthly panel data set, provided by the Federal Employment Agency.[27] The data set comprises information for 178 districts of local employment agencies (LEA) over a period from January 1998 until January 2008. 141 of the 178 LEAs belong to Western and 37 to Eastern Germany. An efficiency analysis based on this data set brings novel insight whether the Hartz reform, especially Hartz IV, has been succesful in raising the matching rates throughout Germany.

To underline the strongly heterogeneous regional labor market in Germany, Table 1 presents the mean values of the hiring rate m_{it} and the exogenous variables entering the stochastic frontier model in equation (2) for overall Germany, the Eastern and the Western part. The hiring rate is measured as the outflow rate from unemployment to employment identified by social security payments. Hence, unemployed who participate in a measure of active labor market policy (ALMP) immediately before they find a job are counted as hirings from out of the labor force, as participants in programs of ALMP are not recorded as unemployed.

It is remarkable that, compared to West Germany, the mean values of the hiring and unemployment rate as well as of the unemployment inflow rate for Eastern Germany are about twice as high. The twofold higher matching rate is likely to be a result of the higher stocks and inflows of unemployed compared to the entire labor force.[28]

The mean values of selected Z_{it}-variables are listed in Table 2 and primilary describe the

[27] The data is publicly available at the website of the Federal Employment Agency (*Bundesagentur für Arbeit*). Please refer to `www.arbeitsagentur.de`

[28] According to studies of the Institute of Employment Research *IAB* in 2007 on average only 49 % of all vacancies are reported to the Federal Employment Agency by German firms. The registration rate in East Germany is somewhat higher with 52 % compared to 48 % for West Germany. More specifically, about 66% of all registered vacancies are to be filled immediately. Although not all vacant jobs are registered, it sufficiently reflects the job placement executed by LEAs and how it has been improved during the previous years.

Table 1: Mean values[1] (1998:01-2008:01)

Variable		Germany	East[2]	West
Hiring rate	m_{it}	0.67%	1.13%	0.55%
Unemployment rate	u_{it}	10.28%	17.89%	8.30%
Vacancy rate	v_{it}	1.07%	0.97%	1.10%
Unemployment inflow rate	u_{it}^F	1.55%	2.45%	1.32%
Vacancy inflow rate	v_{it}^F	0.64%	0.84%	0.59%

[1] The variables are reported as rates using the total civilian labor force as reference category.E.g., the unemployment rate u_{it} has been calculated as the share of the unemployed related to the total civilian labor force in the LEA i at month t.

[2] The abbreviations *East* and *West* stands for Eastern and Western Germany.

structure of the unemployment pool. Again, the unemployment rates for East Germany, except for foreigners, are twice and in case of the female and the long term unemployment rate, nearly three times higher than for West Germany. Despite the structure of the unemployed, two important measures for an ex-ante impression of the German labor market are listed at the end of Table 2: The matching probability and the labor market tightness.

Table 2: Mean values of selected Z_{it}-variables (1998:01-2008:01)

Variable		Germany	East	West
Unemployment rate of the $<$ 25 years	*young*	1.21%	2.03%	0.99%
Unemployment rate of the $>$ 55 years	*old*	1.61%	2.61%	1.35%
Long term unemployment rate	*long*	3.65%	6.56%	2.89%
Female unemployment rate	*fem*	4.84%	9.03%	3.76%
Foreign unemployment rate	*non*	1.11%	0.52%	1.27%
Population Density[1]	*PopDens*	428.15	326.98	454.7
Matching Probability[2]	ϕ	6.93%	6.45%	7.05%
Labor Market Tightness[3]	θ	13.16%	5.63%	15.14%

[1] The population density is reported as the number of people per square kilometer.

[2] The Matching Probability is simply the number of matches per unemployed, given by $\phi = \frac{M}{U}$.

[3] The Labor Market Tightness, denoted as $\theta = \frac{V}{U}$ reflects the number of jobs per unempoyed.

The matching probability ϕ indicates how likely an unemployed worker finds a job. The vacancy-to-unemployed ratio, denoted as $\theta = V/U$, represents an indicator for the labor market tightness or, more precisely, how tight the number of vacancies are distributed per unemployed worker.[29] Given the descriptive statistics in Table 2, the East German labor market seems on average more efficient than the West German labor market. In other words, in West Germany the vacancy stock covers on average[30] 15.14% of all registered unemployed. The probability, that an unemployed gets matched with one of these vacancies during a certain time period, in this case during January 1998 and January 2008, is on average 7.05%. Contrarily, in East Germany merely 5.63% of the unemployed are assigned to exactly one vacant job position, whereas 6.45% of them are likely to get placed in one of the vacant jobs.

4 Estimation Procedure and Results

This section presents the estimation results of several specifications of a stochastic efficiency frontier.[31] I will evaluate the more appropriate functional form for the frontier in section 4.1, the matching efficiencies are computed in section 4.2.[32]

4.1 Selection of the Functional Framework

Initially, the stochastic frontier is estimated in a simple form, where the inefficiency term ϑ_{it} is only a function of time, as shown in equation (14). To allow for comparison, three alternative functional frameworks are estimated: A Cobb-Douglas (CD), a Constant Elasticity of Substitution (CES) and a translog (TL) matching function given through the equations (3)-(5), presented in section 2.1.

The results in Table 3 for the stock-stock and in Table 4 for the stock-flow matching functions are obtained by applying this less sophisticated framework to the data of 178 LEAs across Ger-

[29] The more vacancies per unemployed the tighter the labor market. Given a constant tightness θ, a labor market is said to be more efficient, if its matching probability ϕ is higher than in the other labor market with the same labor market tightness. In other words, given an identical and constant matching probability ϕ, the labor market with the lowest labor market tightness θ is the most efficient.

[30] The average is calculated for the time period from January 1998 until January 2008.

[31] The estimates were carried out with FRONTIER 4.1, a computer program developed by Battese and Coelli (1995).

[32] Basically, there are several ways of computing the matching efficiencies, either based on ordinary least squares or on maximum likelihood estimation. The advantage of the maximum likelihood approach is, that the estimates of the coefficients belonging to the frontier function and the technical efficiencies can be achieved simultaneously.

many between January 1998 and January 2008. Not surprisingly, the stocks of unemployed u and vacancies v enter significantly positive. Except for the translog function (TL), the impact of the unemployment and vacancy rate declines by controlling for the inflow rates of both unemployed u^F and vacancies v^F. An 1%-increase of the vacancy inflow rate contributes to a 23% (59%) higher matching rate in case of the CD-specification (CES). As expected for the stock-stock translog matching function (TL), the coefficient measuring the interaction between unemployed and vacancies of 0.36 is significantly positive with a t-value of 29.07. In other words, 36% of all the hirings are caused by an 1% increase in the interactions of the stocks of unemployed and vacancies, relative to the entire labor force.

Table 3: Stochastic frontier estimation: stock-stock matching model (1998:01-2008:01)

$f(\cdot)$	(CD)	(CES)	(TL)
$\ln u$	0.96	0.90	1.36
	(82.57)	(55.61)	(25.85)
$\ln v$	0.29	0.35	0.93
	(73.36)	(26.49)	(32.85)
$\ln u^2$			-0.003
			(-0.14)
$\ln v^2$			0.08
			(10.48)
$\ln uv$			0.36
			(29.07)
$\ln(u-v)^2$		0.01	
		(4.46)	
$2005:01$	0.12	0.11	0.07
	(6.29)	(5.98)	(4.00)
$cons$	-0.86	-0.86	0.01
	(-15.03)	(-18.85)	(0.37)
σ^2	0.15	0.13	0.1
	(24.32)	(23.99)	(20.24)
γ	0.62	0.59	0.53
	(51.33)	(45.85)	(21.94)
η	0.0015	0.0009	0.0013
	(8.94)	(10.57)	(10.85)
ρ		-0.01	
$LogL$	29.62	12.58	3623.07
N	21314	21314	21314

All models were estimated with 11 monthly dummies. t statistics in parentheses.
γ is obtained by $\gamma = \sigma_\omega^2/(\sigma_\epsilon^2 + \sigma_\omega^2)$. A $\gamma = 0$ implies $\sigma_\omega^2 = 0$ and indicates no variation due to inefficiency.

Subject to the hypothesis, that the stocks are more likely to interact with the inflows, this result turns out to be significantly negative in the stock-flow specification in Table 4. More precisely, the vacancy stock-unemployment inflow vu^F and the unemployment stock-vacancy inflow uv^F interactions enter significantly positive, whereas the interactions among the stocks uv or the flows $u^F v^F$ have a significantly negative impact on the hiring rate.

Table 4: Stochastic frontier estimation: stock-flow matching model (1998:01-2008:01)

$f(\cdot)$	(CD)	(CES)	(TL)
$\ln u$	0.51	0.22	1.75
	(52.07)	(6.95)	(15.02)
$\ln v$	0.10	0.11	0.77
	(20.81)	(4.75)	(12.23)
$\ln u^F$	0.45	0.32	-1.08
	(53.97)	(10.81)	(-14.62)
$\ln v^F$	0.23	0.59	0.75
	(44.62)	(23.26)	(11.37)
$\ln u^2$			-0.42
			(-16.19)
$\ln v^2$			-0.01
			(-0.92)
$\ln(u^F)^2$			-0.60
			(-22.20)
$\ln(v^F)^2$			0.08
			(5.26)
$\ln uv$			-0.08
			(-4.02)
$\ln uu^F$			0.86
			(18.88)
$\ln uv^F$			0.26
			(8.99)
$\ln vu^F$			0.27
			(9.57)
$\ln vv^F$			0.10
			(5.16)
$\ln u^F v^F$			-0.17
			(-5.52)
2005 : 01	-0.003	0.11	0.09
	(-0.18)	(6.25)	(5.05)
cons	-0.14	0.10	0.48
	(-3.75)	(2.35)	(11.74)
LogL	2535.76	2899.84	3502.06
N	21314	21314	21314

All models were estimated with 11 monthly dummies. t statistics in parentheses.

The γ-coefficient corresponds to the variance σ^2_ω of the inefficiency term ϑ_{it}. Explicitly, it states how much of the overall variance is explained by inefficiency controls. For the stock-stock model it ranges from 53% for the translog framework (TL) up to 62% in the case of a Cobb-Douglas specification (CD).[33] In contrast, the γ-value of 0.44 (0.34) for the stock-flow model is the highest (lowest) for the TL-specification (CD). η indicates an increasing matching inefficiency over time, as the coefficients for all specifications are significantly positive.[34]

Table 4 (continued): Stochastic frontier estimation: stock-flow matching model (1998:01-2008:01)

	(CD)	(CES)	(TL)
σ^2	0.07	0.07	0.07
	(27.75)	(22.48)	(28.85)
γ	0.34	0.39	0.44
	(20.33)	(16.37)	(26.74)
η	0.0033	0.0026	0.0018
	(23.91)	(13.26)	(24.98)
ρ_1		-0.02	
ρ_2		0.18	
ρ_3		-0.47	
ρ_4		0.51	
ρ_5		-0.40	
ρ_6		0.09	
$LogL$	2535.76	2899.84	3502.06
N	21314	21314	21314

All models were estimated with 11 monthly dummies. t statistics in parentheses.
γ is obtained by $\gamma = \sigma_\omega^2/(\sigma_\epsilon^2 + \sigma_\omega^2)$. A $\gamma = 0$ implies $\sigma_\omega^2 = 0$ and indicates no variation due to inefficiency.

Furthermore, the values of the log-likelihood function for the stock-stock as well as for the stock-flow matching function conspiciuously favor the translog function as the proper functional framework to model the matching processes by a stochastic efficiency frontier.[35]

[33] 53% of the overall variance is explained by ineffciency in a functional framework specified by a translog function.

[34] See equation (14) for a formal derivation of this result.

[35] The likelihood ratio test (LR), which specfies that the translog function is the best model compared to the nesting Cobb-Douglas and CES-function, cannot be rejected.

4.2 The Stochastic Translog Frontier and Inefficiency Estimates

Table 4.2 displays the estimation results of a stochastic translog frontier like the Battese and Coelli specification in equation (11), presented in section 2.2.

So far, as outlined in the literature review, no other study examines the impact of stocks and flows and their interactions on labor market matching by applying a stochastic translog frontier. However, to enable a comparison with studies considering solely the stocks, I also estimate the Battese and Coelli specification for the stock-stock matching model (1) in Table 4.2. Similar to the studies of Fahr and Sunde (2006) for Germany, Hynninen (2009) for Finland and Ibourk et al. (2004) for France, the stocks of unemployed and vacancies turn out to be signifcantly positive. However, in contrary to Ibourk et al. (2004), the interaction of stocks of unemployed and vacancies exhibits with a coefficient of 0.4 and a t-value of 32.62 a highly significantly positive impact on the hiring rate. Furthermore, the findings of Ibourk et al. (2004) suggest a concave behavior of the vacancy stock. As the coefficient of the quadratic term of the vacancy rate v^2 is 0.11 significantly positive in Table 4.2, I do not find support for their results. The results for the stock-flow model (2) barely differ from those obtained by the estimation of the stock-flow specification (TL) without the modeled inefficiency term in Table 4. The significantly positive impact of the stock-flow interactions on the hiring rate remains unchanged as opposed to the either not significant or negative impact of the stocks and flows taken seperately.

The columns (1') and (2') in Table 4.2 present the estimates of the determinants of the matching inefficiency. Except for the rate of unemployed above the age of 55 (*old*) in case of the stock-flow specification (2), all variables used to significantly explain inefficiency very well. Surprisingly, the long-term unemployment rate positively influences the matching efficiency. Probably this result coincides with the positive impact of the Hartz IV reform, measured by the exponential Hartz IV dummy. The Hartz IV coefficients of both the stock-stock (1) and stock-flow (2) model enter significantly negative, indicating an inefficiency decreasing effect. Apparently, the implementation of the Hartz IV law reveals a partial contribution to a higher matching efficiency.

As in Coles and Smith (1996), population density definitely matters in the application process for the unemployed. Intuitively, the higher population density is, the matching or placement

Table 5: Stochastic Translog Efficiency Frontier (1998:01-2008:01)

$f(\cdot)$	(1)	(2)	Z_{it}	(1')	(2')
$\ln u$	1.88	1.59	*young*	-0.07	-0.11
	(36.60)	(16.20)		(-4.94)	(-8.82)
$\ln v$	1.10	0.80	*old*	0.12	0.01
	(37.14)	(12.95)		(9.87)	(0.80)
$\ln u^F$		-0.73	*long*	-0.11	-0.03
		(-9.29)		(-15.14)	(-3.67)
$\ln v^F$		0.74	*fem*	0.50	0.42
		(10.78)		(18.40)	(16.65)
$\ln u^2$	0.28	-0.13	*non*	0.19	0.14
	(15.56)	(-5.45)		(38.37)	(30.74)
$\ln v^2$	0.11	-0.004	*ifo*	-0.01	-0.01
	(14.47)	(-0.39)		(-10.63)	(-13.2)
$\ln(u^F)^2$		-0.50	*HartzIV*	-0.16	-0.11
		(-17.01)		(-15.90)	(-12.60)
$\ln(v^F)^2$		0.10	*PopDens*	0.33	0.22
		(6.33)		(12.21)	(8.84)
$\ln uv$	0.40	-0.02	*PopDens*2	-0.02	-0.01
	(32.62)	(-0.93)		(-9.87)	(-6.82)
$\ln uu^F$		0.64	*East*	-0.29	-0.16
		(13.64)		(-20.41)	(-13.52)
$\ln uv^F$		0.17	*Trend*	0.001	-0.001
		(6.07)		(6.85)	(-3.99)
$\ln vu^F$		0.29	*cons*	0.72	0.71
		(9.86)		(6.63)	(7.27)
$\ln vv^F$		0.07			
		(3.32)			
$\ln u^F v^F$		-0.15			
		(-4.67)			
2005 : 01	0.06	0.09			
	(3.19)	(4.52)			
cons	0.60	0.55			
	(10.02)	(10.91)			
σ^2	0.06	0.05			
	(100.26)	(92.73)			
γ	0.28	0.19			
	(15.24)	(10.70)			
LogL	971.72	3013.62			
N	21314	21314			

All models were estimated with 11 monthly dummies. t statistics in parentheses.

γ is obtained by $\gamma = \sigma^2_\omega/(\sigma^2_\epsilon + \sigma^2_\omega)$. A $\gamma = 0$ implies $\sigma^2_\omega = 0$ and indicates no variation due to inefficiency.

(1) stock-stock translog frontier and the corresponding inefficiency coefficients in (1'). (2) stock-flow frontier and (2') stock flow inefficiency coefficients.

process is less efficient. A low unemployment rate does not always go in line with an efficient placement procedure of the LEAs. Evidence for it, can be found with the significantly positive coefficient of 0.33 for the stock-stock (1') and 0.22 for the stock flow model (2'). However, due to negative coefficients of -0.02 (1') and -0.01 (2') both with t-values wide above 3, there seems to be congestion effects. Hence, as population density exeeds a certain limit, a larger population density contributes to a slightly increased matching efficiency. Probably this result can be explained by a kind of placement routine, which has been evolved in LEAs in densely populated regions.

The γ-values for the stochastic translog frontier drops to 28% and to 19% for the stock-stock and stock-flow specification, respectively.[36] Thus, given the variables which are supposed to explain the inefficiency, only 28% (19%) of the variance due to inefficiency σ_{ω}^2 is left unexplained, whereas the rest of the overall variance counts as stochastic. Compared to other studies, the γ-estimates broadly differ. For instance, Fahr and Sunde (2009) obtained a γ of 0.81.[37] Ibourk et al. (2004) estimate that 61% of the overall variance is due to matching inefficiencies, whereas Hynninen (2009) finds an insignificant γ-value of zero.[38]

4.3 Regional Efficiency Estimates

The ranking of the 10 regions assigned to one of the 178 local employment agencies, exhibiting the five highest or the five lowest matching efficiencies conditional on the estimates of the stock-stock model (stock-flow model) are displayed in Table 6 (Table 7). To allow for comparison with the results obtained by Fahr and Sunde (2006), I include the efficiency estimates conditional on the Cobb-Douglas and CES frontier specification. Hereby it is important to mention, that the Cobb-Douglas (CD), the CES (CES) and the translog (TL^1) frontier functions are estimated

[36] Contrary to model (2), the time trend enters significantly negative in the stock-stock model (1), indicating a decreasing matching efficiency over time. This may imply, that the placement process of the stocks of unemployed (mainly long-term unemployed) with the vacancy stock shall be improved further on.

[37] Fahr and Sunde (2006) include the stock and the fraction of older and younger unemployed, those with a low and a high education level, respectively, the labor market tightness and a time trend. Hence, they left out control variables for female, foreign and long-term unemployed. As their analysis is restricted to the Western part of Germany, they leave out the dummy variable to control for the strong deviations with regard to the unemployment rate, especially with respect to the problem key groups, such as long-term, female, foreign, older and younger unemployed.

[38] A γ-value of zero indicates that all deviations from the frontier function are not due to inefficiencies. In this case, the model collapses to a standard regression model, estimated by OLS.

without an explicit modeling of the inefficiency term as shown in equation (14). The last column in Tables 6 and 7 displays the regional matching efficiencies based on the estimated stochastic translog specification including the Z-variables to model the ineffcinecy term.

Table 6: Average Efficiency Estimates for the stock-stock matching model - Germany (1998, 2007)

model	(CD)		(CES)		(TL^1)		(TL^2)	
rank	region	1998[a]	region	1998	region	1998	region	1998
1	Ansbach	0.94	Ansbach	0.97	Plauen	0.97	Stralsund	0.97
2	Traunstein	0.89	Traunstein	0.92	Neubrandenburg	0.95	Neubrandenburg	0.97
3	Kempten	0.88	Kempten	0.91	Traunstein	0.92	Frankfurt a.O.	0.96
4	Weilheim	0.84	Weilheim	0.87	Annaberg-Buchholz	0.88	Neuruppin	0.96
5	Freising	0.79	Passau	0.8	Altenburg	0.87	Stendal	0.96
174	Helmstedt	0.31	Düren	0.32	Wuppertal	0.39	Göppingen	0.42
175	Gelsenkirchen	0.29	Bochum	0.31	Dortmund	0.38	Ludwigsburg	0.4
176	Essen	0.29	Essen	0.3	Darmstadt	0.38	Berlin Süd	0.37
177	Bochum	0.29	Gelsenkirchen	0.3	Frankfurt a.M.	0.37	Berlin Nord	0.37
178	Dortmund	0.26	Dortmund	0.27	Düren	0.36	Berlin Mitte	0.37
rank	region	2007[a]	region	2007	region	2007	region	2007
1	Ansbach	0.94	Ansbach	0.97	Plauen	0.97	Stendal	0.97
2	Traunstein	0.9	Traunstein	0.93	Neubrandenburg	0.95	Neubrandenburg	0.97
3	Kempten	0.89	Kempten	0.92	Traunstein	0.93	Wittenberg	0.96
4	Weilheim	0.86	Weilheim	0.88	Annaberg-Buchholz	0.9	Stralsund	0.96
5	Freising	0.8	Freising	0.82	Gotha	0.89	Frankfurt a.O.	0.95
174	Helmstedt	0.34	Düren	0.36	Wuppertal	0.44	Frankfurt a.M.	0.45
175	Bochum	0.33	Bochum	0.34	Dortmund	0.43	Offenbach	0.43
176	Gelsenkirchen	0.32	Gelsenkirchen	0.33	Darmstadt	0.43	Hanau	0.43
177	Essen	0.32	Essen	0.33	Frankfurt a.M.	0.42	Düren	0.4
178	Dortmund	0.29	Dortmund	0.31	Düren	0.41	Wiesbaden	0.39

The regional matching efficiencies are computed from the estimated frontier specifications in Table 3.
[1] ([2]) Efficiency estimates from a stochastic translog frontier without (with) modelling the inefficiency ϑ_{it}.
[a] The matching efficiency is ranked according to the average for the years 1998 and 2007, respectively.

Apparently, the results for the stock-stock and the stock-flow matching model for the Cobb-Douglas (CD) as well as for the CES (CES) frontier do not strongly differ. Whereas regions in Bavaria close to the Czech or Austrian borders or nearby Munich (Ansbach, Freising, Kempten, Passau, Traunstein, Weilheim) belong to the five regions possessing the most efficient matching performance. Those regions exhibiting the lowest matching efficiency are in North Rhine-Westphalia in the Ruhr Area (Bochum, Dortmund, Essen, Gelsenkirchen). These results coincide with those found by Fahr and Sunde (2006).[39]

[39] Fahr and Sunde (2006) compute the regional matching efficiencies based on the estimates for all matches from non-employment, for matched from the home region, from neighbor as well as from non-neighbor regions.

Table 7: Average Efficiency Estimates for the stock-flow matching model - Germany (1998, 2007)

model	(CD)		(CES)		(TL^1)		(TL^2)	
rank	region	1998[a]	region	1998	region	1998	region	1998
1	Ansbach	0.99	Ansbach	0.98	Traunstein	0.91	Stralsund	0.96
2	Kempten	0.98	Kempten	0.96	Ansbach	0.88	Neubrandenburg	0.96
3	Traunstein	0.94	Traunstein	0.92	Passau	0.88	Eberswalde	0.94
4	Weilheim	0.93	Weilheim	0.89	Kempten	0.86	Stendal	0.94
5	Freising	0.87	Passau	0.87	Weilheim	0.82	Neuruppin	0.94
174	Ludwigshafen	0.41	Köln	0.41	Essen	0.4	Frankfurt a.M.	0.49
175	Köln	0.4	Essen	0.4	Frankfurt a.M.	0.39	Ludwigsburg	0.49
176	Essen	0.4	Bochum	0.39	Bochum	0.39	Berlin Nord	0.46
177	Bochum	0.39	Gelsenkirchen	0.39	Dortmund	0.39	Berlin Süd	0.46
178	Dortmund	0.38	Dortmund	0.38	Ludwigshafen	0.38	Berlin Mitte	0.46
rank	region	2007[a]	region	2007	region	2007	region	2007
1	Kempten	0.99	Ansbach	0.99	Traunstein	0.93	Neuruppin	0.97
2	Ansbach	0.99	Kempten	0.97	Ansbach	0.92	Stendal	0.97
3	Traunstein	0.96	Traunstein	0.94	Passau	0.91	Neubrandenburg	0.97
4	Weilheim	0.95	Weilheim	0.92	Kempten	0.9	Wittenbrg	0.97
5	Freising	0.91	Passau	0.9	Weilheim	0.87	Stralsund	0.97
174	Köln	0.53	Köln	0.51	Essen	0.52	Göppingen	0.58
175	Gelsenkirchen	0.53	Essen	0.5	Dortmund	0.51	Wiesbaden	0.58
176	Bochum	0.52	Gelsenkirchen	0.49	Frankfurt a.M.	0.51	Ludwigsburg	0.57
177	Essen	0.52	Bochum	0.49	Bochum	0.51	Mannheim	0.56
178	Dortmund	0.5	Dortmund	0.48	Ludwigshafen	0.5	Offenbach	0.55

The regional matching efficiencies are computed from the estimated frontier specifications in Table 4.
[1] ([2]) Efficiency estimates from a stochastic translog frontier without (with) modelling the inefficiency ϑ_{it}.
[a] The matching efficiency is ranked according to the average for the years 1998 and 2007, respectively.

They identify rural and thinly populated regions in Northern Germany or regions around Munich with a performance ranked among the top five regions with the highest matching efficiencies. In case of the stock-flow translog frontier model in the third column of Table 7 (TL^1), these results do not change, whereas they do for the stock-stock specification in Table 6. For the stock-stock specification, regions from Eastern Germany enter the Top 5 positions of the matching efficiency. This picture appears somewhat distorted since the regions do not belong to only one federal state. In column (TL^1) of table 6 Annaberg-Buchholz and Plauen (both located in Saxony), Neubrandenburg (Mecklenburg Pomerania) and Altenburg (Thuringa) in 1998 and Gotha (Thuringa) instead of Altenburg in 2007 belong to the most efficient regions in Germany. Since I do not restrict my analysis to Western Germany, as do Fahr and Sunde (2006), but examine the Eastern part as well, these results might be a probable consequence for the stock-stock translog frontier. Obviously, the interactions between the stocks of unemployed and vacancies exhibit a higher matching efficiency for these regions in Eastern Germany than the interactions between the stocks and flows of both vacancies and unemployed.

Furthermore, the last column (TL^2) in Tables 6 and 7 refer to the matching efficiencies conditional on the estimates of the Battese and Coelli specification denoted in equation (12). Somewhat surprisingly for both specifications the stock-stock and the stock-flow model, regions from Eastern Germany seem to be most efficient (Stralsund, Neubrandenburg, Stendal, Neuruppin, Frankfurt (Oder)). All these regions have certain characteristics in common: thinly populated, located close to the Polish border, near major cities, e.g. Berlin. On the other hand, the local employment agencies for Berlin (1201, 1202, 1203) rank amongst those with the lowest average matching efficiency in 1998. By revising the average matching efficiencies for 2007, however, Berlin experienced an increase in its matching performance. Therefore, regions from Hesse (Frankfurt (Main), Offenbach, Wiesbaden) and from Baden-Württemberg (Ludwigsburg, Mannheim) enter in 2007 the five positions at the end of the ranking.

5 Conclusion

Since the sequentially implemented Hartz laws - as a major part of a comprehensive labor market reform - in Germany, there has been a huge interest to evaluate their effects on labor market outcomes, such as the transition from unemployment to employment embodied by the usual matching function framework. As opposed to the last law (Hartz IV), an extensive evaluation of the first three laws (Hartz I - Hartz III) has already taken place. Hartz IV was especially aimed at improving the efficiency of the placement process as well as the willingness of the (long-term) unemployed to accept moderate job offers. Hence, this paper addresses an analysis of the change in the matching efficiency across regional labor markets in the course of the reform. In particular, this article pursues two aims: First, to estimate the impact of stocks and flows of vacancies and unemployed and their interactions as well as the impact of potential sources of inefficiency on the regional matching rate. Second, to compute the regional matching efficiencies based upon the estimates obtained in the first step. I achieve this by employing a stochastic translog frontier to data on 178 German local employment agencies covering the period from January 1998 until January 2008. More specifically, using this approach, the disaggregated hiring rate becomes a stochastic function of the determinants of the variables accounting for the behavior of unemployed workers and worker-seeking firms.

In following the technique proposed by Battese and Coelli (1995), I identify a proper stochastic frontier function and a stochastic inefficiency term. The inefficiency term is composed of a set of variables supposed to explain the inefficiency. As opposed to a deterministic frontier, not all unusual observations have been counted as inefficiency increasing or decreasing, but instead as outliers. According to the estimation results of a simpler version of the stochastic frontier, the translog function appears to be the more appropriate functional framework compared to the commonly employed Cobb-Douglas approach and the CES-function.

Furthermore, I estimate two specifications of the matching function: A stock-stock and a stock-flow model. According to the hypothesis postulated earlier, the interactions between the stock of unemployed and the vacancy inflow as well as between the vacancy stock and the unemployed inflow exhibit a larger impact on the hiring rate than the interaction between stocks and stocks or flows and flows.

To examine whether Hartz IV has led to an increased matching efficiency in Germany, an *exponential* dummy variable is added alongside other variables, among them the unemployment rate for younger, long-term, female and foreign unemployed in the stochastic translog frontier specification. Addionally, matching efficiencies have been computed and ranked for all the local employment agencies. My findings reveal that the implementation of the Hartz IV law exhibits a significantly positive impact on the matching efficiency for both specifications: the stock-stock and the stock-flow model. The fraction of older, female and foreign unemployed appears as efficiency decreasing, whereas the younger and, surprisingly, the long-term unemployed exhibit a significantly positive impact on labor market matching.

Summing up, the stochastic translog frontier appears as a promising framework to model the matching process including the stocks and flows of the unemployed and of vacancies. The twofold structure of this approach - the frontier function and the inefficiency term - allows for an extensive examination of the matching (in)efficiency and its changes in the course of certain reforms or shocks occured in the labor market.

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