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Markus Frölich
Patrick A. Puhani

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Markus Frölich
SIAW, University of St. Gallen

Patrick A. Puhani
MIT, Cambridge, SIAW, University of St. Gallen, CEPR, London,
ZEW, Mannheim, WDI, University of Michigan Business School and IZA, Bonn

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IZA

P.O. Box 7240
D-53072 Bonn
Germany

Tel.: +49-228-3894-0
Fax: +49-228-3894-210
Email: iza@iza.org

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ABSTRACT

Immigration and Heterogeneous Labor in Western Germany
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This paper presents a methodology to identify net demand shocks as well as wage rigidities in heterogeneous labor markets on the basis of nonparametric regression. We show how this approach can be used to make suggestions for immigration policy in economies with labor market rigidities. In an application to western Germany it is demonstrated that nonparametric regression is feasible in higher dimensions with only a few thousand observations. In sum, labor markets able to absorb immigrants are characterized by above average age and by professional occupations. On the other hand, labor markets for young workers in service occupations are identified to exhibit rising unemployment due to wage rigidities and are therefore not recommended for immigration.

JEL Classification: C14, J31, J61, J64, J68

Keywords: Wage, unemployment, migration, rigidity, nonparametric regression

Patrick A. Puhani
Dept. of Economics
50 Memorial Drive
MIT, E52-251D
Cambridge, MA 02142-1347
U.S.A.
Tel.: +1-617-253-8556
Fax: +1-617-253-6915
Email: Puhani@mit.edu

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Non-Technical Summary

Immigration policy has been receiving significant attention in Germany recently. The current government plans to pass an immigration law. This marks a turning point in German politics, as Germany has previously declared itself as a 'non-immigration country'. An important feature of the conceived new immigration policy is its selectivity. Because of potential public concerns about labor market competition by immigrants, the government proclaims to allow only people in for whom there is a 'labor shortage'. Hence, it seems that a point system for immigration, which assigns applicants certain points depending on their socio-economic characteristics and admits these applicants once they pass a certain threshold, would be politically feasible in the near future. Such point systems have been implemented in Australia, Canada, and New Zealand, and have been proposed for the United States.

In this paper, we present an econometrically substantiated analysis of German labor markets from which one can draw suggestions on which types of labor should be allowed to immigrate and which ones should not. To this end, we adopt a nonparametric approach to estimating wage and unemployment developments for labor markets defined on the basis of observable characteristics. (To our knowledge, our paper is one of the first applications of nonparametric regression in higher dimensions in labor economics.) Unlike the point system, this methodology does not allocate a fixed number of points for, say, a certain age group, but determines the 'immigration yes' or 'no' suggestion directly for any given combination of observable characteristics. This may be preferable to a point system, as it allows the benefit of being in a certain age group to *vary* with, for example, the occupational qualification.

For a complete summary of our classification analysis, the reader may refer to the internet page http://www.siaw.unisg.ch/wagemonitor, where he or she obtains the estimated classification for specific labor markets. To sum up, 'immigration yes' labor markets are characterized by above-average shares of *experienced, professional,* as well as *service sector* labor. The region over-represented in these markets is *Rhein-Hessen-Saar-Pfalz*. 'Immigration no' labor markets, on the other hand, often exhibit below-average *experience*, and an over-representation of *males*, occupation as *service workers*, the *industry sector*, and the state of *Nordrhein-Westfalen*. These results comply

with the current German government’s view that highly qualified people should be preferred for immigration. However, there may be a trade-off between accepting experienced workers as immigrants and the wish to take in young people in order to bolster future payments into Germany’s ailing social security system (*cf.* Zimmermann *et al.*, 2001). These aggregated results, however, do not necessarily imply conflicting aims, since the heterogeneity of labor markets is large. Hence, there are labor markets for both low age and for high age workers which are suited for immigration. Looking at means only does not do justice to the ample heterogeneity found between the labor markets in a modern economy. Hence, analysis of heterogeneity, *e.g.* through nonparametric regression as carried out in this paper, deserves more attention than it often receives.

We believe that a permanent tracking of labor markets at a detailed level by a method as presented in this paper can serve as a useful information tool to monitor immigration policies. Furthermore, we demonstrate that the large majority of the ‘immigration no’ markets are facing real wage rigidities. This empirical result substantiates the importance of taking wage rigidities into account when formulating immigration policies in European countries (*cf.* theoretical studies cited in the Introduction). Furthermore, because we find regional differences in the ‘immigration aptitude’ of labor markets, we argue that immigration does not have to be regulated at the federal level. States or regions may well decide whether they favor temporary immigration or not. Such a decentralized approach to immigration would probably require a temporary regional residence permit for immigrants, similar to the one of Switzerland, for example.

1 Introduction

The analysis of immigration and its effects on the labor market has received considerable interest in the economic literature. However, the reverse question on how immigration should be guided or regulated on the basis of the labor market situation in the host country has not enjoyed much attention. In this paper, we propose a methodology for assessing the immigration aptitude of particular labor markets. The approach is based on classifying labor markets according to exhibited wage rigidities. To fully appreciate the heterogeneity of labor, we propose a nonparametric estimator as the basis for classification.

In general terms, immigration increases aggregate welfare of the host country if labor markets are competitive, because the gains to capital exceed the losses of native labor (*cf.* Borjas, 1999a). However, the welfare effects of immigration are less clear in an economy with rigid labor markets, *e.g.* due to collective wage bargaining, or in the presence of a generous social security system as in many European countries (*cf.* Brecher and Choudri, 1987; Fuest and Thum, 2000; 2001; Schmidt, Stilz, and Zimmermann, 1994). But even with positive aggregate effects, immigration may be accompanied by a substantial income redistribution from labor to capital. If lump-sum taxes are not available, it is difficult to assess whether immigration is beneficial. Furthermore, in modern economies labor is extremely heterogeneous (much beyond a simple distinction between skilled and unskilled) and different labor types are affected differently by the skill composition of the immigrants. It is thus not surprising that the distributional consequences of immigration fare prominently in public debates (*cf.* Johnson, 1980). This controversy is also reflected in the restrictive immigration policies found in many countries. Also, selective immigration policies such as the 'points systems' in Australia, Canada, and New Zealand, which control immigrant flows on basis of age, education, occupation *etc.* (*cf.* Antecol, Cobb-Clark, and Trejo, 2001; Bauer, 1998; Borjas, 1999b), are intended to contain immigration which may increase wage dispersion. By preferring mainly skilled labor, these regimes favor immigrants who pay more taxes and rely less on social transfers (see *e.g.* Borjas 1999b). However, if labor markets are non-competitive, selective immigration policies should also take account of potential wage rigidities.

Numerous empirical studies estimate impacts of immigration on wages and employments rates (*e.g.*, Altonji and Card, 1991; Angrist, 1996; Borjas, Freeman, and Katz, 1997; Card, 1990; 2001; De New and Zimmermann, 1994; Gang and Rivera-Batiz, 1994; Hunt, 1992; Pischke and Velling, 1997; Winter-Ebmer and Zweimüller, 1996; for surveys see also Friedberg and Hunt, 1995; Borjas, 1999a). However, these studies are not directly instructive for selective immigration policies, since they provide only highly aggregated results and do not take much account of heterogeneous labor (see Card, 2001, for an exception).

A natural basis for guiding selective immigration would be to prefer immigration in labor markets where demand is rising faster than supply. In such markets it is more likely that real wages will not fall in the face of increased competition from immigrants. Also, immigrants destined for such labor markets stand better chances finding a job instead of drawing social security benefits. On the other hand, labor markets plagued by rising unemployment should not be opened up to immigration, since the immigrants attached to these labor markets are more likely to become unemployed or cause unemployment among natives. Extending on these considerations, we propose a method for guiding a selective immigration policy for Germany by identifying labor markets suitable for immigration on the basis of recent labor market developments. Germany is particularly interesting, since - in spite of rigid labor markets and high and rising unemployment - there are frequent complaints by employers about 'labor shortages' of skilled labor. As a result, Germany is considering the introduction of a selective immigration scheme. Using the identification strategy for wage rigidities of Puhani (2001) we investigate labor market developments between 1992 and 1998 and classify labor markets with increasing net demand as suitable for immigration and markets with decreasing net demand as unsuited.

Our particular focus in this paper is on the *heterogeneity* of labor. Compared to, for example, Altonji and Card, (1991), Bound and Johnson (1992), Card, Kramarz, and Lemieux (1999) Kahn, (2000), Katz and Murphy (1992), Krueger and Pischke (1997) or Murphy and Welsh (1992), we consider heterogeneity in greater detail. Distinctively, we estimate wage and unemployment risk developments by *nonparametric regression* for very specific labor markets defined by age, education, gender, occupation and sectoral background as well as region. Expected wages and unemployment risk are estimated by local linear (*cf.* Fan, 1992; Hastie and Loader, 1992) and local logit regression (*cf.* Frölich, 2001), respectively, which both belong to the framework of local parametric regression (Gozalo and Linton, 2000). Nonparametric regression is often considered as unreliable in higher dimensions compared to parametric regression, due to the 'curse of dimensionality'. But, this argumentation is based on comparing nonparametric regression to a correctly specified parametric model. In most applications, however, the true regression curve is unknown, and recent Monte-Carlo results suggest that nonparametric regression with data-driven bandwidth selection outperforms misspecified parametric regression even in higher dimensions and is not much worse in case the parametric model is correctly specified. In particular, nonparametric local linear or local logit regression avoids the inconsistency of misspecified parametric estimators and the inefficiency of the cell-mean or frequency estimator (Racine and Li, 2000). An alternative semiparametric estimator such as Klein and Spady (1993) would also be suitable to our problem. However, local logit was more successful in accommodating heterogeneity in Frölich (2001) than the Klein and Spady estimator. For incorporating discrete and continuous regressors we employ the hybrid kernel developed by Racine and Li (2000). To our knowledge, our paper is one of the first applications of nonparametric regression in higher dimensions in labor economics. The only other studies we are aware of are the ones by Racine and Lee (2000), Millimet and Racine (2001), and Frölich (2001).

Section 2 presents the theoretical framework underlying our empirical analysis. We discuss an identification strategy for wage rigidities and assess which labor markets are suitable for immigration. Section 3 outlines the nonparametric regression techniques employed and Section 4 presents the estimation and labor market classification results for western Germany. Whereas the immigration recommendations are discussed in Section 4, the full results from our nonparametric estimates are available on www.siaw.unisg.ch/wagemonitor. We focus on western Germany, as the labor markets in eastern Germany are characterized by massive government intervention which may distort our statistical measurement. Section 5 concludes.

2 A Simple Model of the Labor Market with Heterogeneous Labor

As a basis for reasoning in which labor markets immigration would be appropriate we want to classify markets according to whether they are 'increasing' or 'decreasing' in 'net demand'. Furthermore, the existence of wage rigidities causing unemployment will come to bear when deciding about immigration. Markets where demand is increasing faster than supply and where real wages are rising are likely to absorb immigrants more easily than labor markets which experience rising unemployment and stagnant or falling real wages.

We propose an empirical strategy based on the supply-demand-institutions framework of Katz and Autor (1999) and adapted to the identification of wage rigidities by Puhani (2001). Suppose there are L different heterogeneous labor markets, and let any particular labor market l be characterized by a set of skills or characteristics.[1] Let

$$D_t = D_t\left(\mathcal{W}_t, Z_t\right) \qquad (L\times 1 \text{ vector of labor demands})$$

$$S_t = S_t\left(\mathcal{W}_t, Z_t\right) \qquad (L\times 1 \text{ vector of labor supplies})$$

denote the labor demand and labor supply functions at time t, given the vector of wage rates $\mathcal{W}_t$ and a vector Z_t of 'shift factors', which might affect labor demand and/or supply. These shift factors may include macroeconomic factors such as the business cycle, interest rates, technological change, the tax structure or changes in the educational composition as well as specific factors related to the labor market such as specific labor market regulations. Notice that D_t and S_t as well as $\mathcal{W}_t$ are column vectors of dimension $L\times 1$ that contain demand, supply and wage rates for all markets, respectively. Hence demand and supply in any labor market l depend on the wage rates in all labor markets. If labor markets are perfectly competitive and an equilibrium exists, wages $\mathcal{W}_t$ should clear all markets such that $D_t = S_t$. In this case, no unemployment would exist. On the other hand, if markets are imperfect, unemployment may occur through a number of reasons, either due to market frictions (*e.g.* incomplete information or transaction costs) or due to institutional reasons causing wage adjustment rigidities (*e.g.* unions, minimum wages, rigid pay scales *etc.*). For immigration policy we are particularly interested in identifying wage rigidities and define the (hypothetical) unemployment rates $\mathcal{U}_{rigid,t}$ as the unemployment rates that would be generated by the wage setting institutions in the absence of frictions:

[1] In the limit, as every person is an individual, one can think of as many labor types L as there are people in the labor market. However, this does not imply that it is interesting for our purpose to classify as many labor markets as there are persons: if there are some people who are (almost) perfect substitutes, these people will operate in the same labor market. Hence although all people are heterogeneous, the only heterogeneity which matters for our study is whether any two types of labor supplied in a 'local' market are sufficiently imperfect substitutes. We do not attempt to estimate the substitutability of various labor types. Instead, we classify labor types on *a priori* reasoning according to a set of observed characteristics which we believe form sufficient homogeneity within and heterogeneity between groups (*cf.* Card, 2001, p. 32).

$$\mathcal{U}_{rigid,t} = \frac{(S_t - D_t)}{S_t} = 1 - \frac{D_t(\mathcal{W}_t, Z_t)}{S_t(\mathcal{W}_t, Z_t)} = \mathcal{U}_{rigid,t}(\mathcal{W}_t, Z_t) \qquad (L\times 1 \text{ vector of latent unemployment rates}).$$

Unemployment due to rigid wages is seen as a form of quantity rationing which may exist if wages are not allowed to settle at the market clearing rate (*cf.* Maddala, 1983). In the presence of (additional) labor market frictions, however, the observed unemployment rates

$$\mathcal{U}_{observed,t} = \varphi_t(\mathcal{U}_{rigid,t}, \gamma_t) \qquad (L\times 1 \text{ vector of observed unemployment rates})$$

are larger than the unemployment rates due to rigidities $\mathcal{U}_{rigid,t}$ and depend on factors γ_t which influence the extent of labor market frictions. (Again, $\mathcal{U}_{rigid,t}$ and $\mathcal{U}_{observed,t}$ are defined as vectors containing the unemployment rates of all L labor markets.) Yet, as market frictions may be of different extent in different labor markets, $\mathcal{U}_{rigid,t}$ and thus the absolute level of rigidity are not identified. This precludes using observed unemployment rates as measures for the extent of labor market rigidities. Consequently, we follow the proposal by Puhani (2001) for identifying *changes* in wage rigidities via concurrent movements in observed unemployment rates and observed wages over time. If this approach is applied to a period where unemployment is initially low but higher later, the identification of labor markets with *changes* in wage rigidities identifies rigidities in all labor markets which experience negative net demand shocks.

The main identifying assumption for detecting wage rigidities is that changes over time in the observed unemployment rate and the (hypothetical) rigid unemployment rate move in the same direction, which seems reasonable if there are no exogenous shocks to market frictions. Precisely, it is assumed that for each labor market l

$$\operatorname{sgn}\left(\Delta_t^{t+\tau}\mathcal{U}_{observed}^l\right) = \operatorname{sgn}\left(\Delta_t^{t+\tau}\mathcal{U}_{rigid}^l\right)$$

holds, where *sgn* is the sign function, $\mathcal{U}_{observed}^l$ and $\mathcal{U}_{rigid}^l$ refer to labor market *l*, and $\Delta_t^{t+\tau}\mathcal{U}$ is the difference between $\mathcal{U}_{t+\tau}$ and $\mathcal{U}_t$. This assumption requires that any changes in the unemployment rate due to wage setting rigidities are not completely offset (or even overcompensated) by opposite movements in the frictional unemployment element. Yet, it is allowed that shocks in the rigid unemployment rate are mitigated by adjustments in frictional unemployment.

With this assumption changes in observed unemployment rates identify the sign of the change in unemployment due to wage rigidities. Furthermore, changes in the rigid unemployment rate can be decomposed into an 'own-wage effect', 'cross-wage effects' and effects due to changes in the 'shift factors' Z_t by using a Taylor series approximation:

$$\Delta_t^{t+\tau}\mathcal{U}_{rigid}^l \approx \underbrace{\mathcal{U}_{\mathcal{W}}^{l,l}\cdot\Delta_t^{t+\tau}\mathcal{W}^l}_{\textit{own wage effect}} + \underbrace{\underbrace{\sum_{j\neq l}\mathcal{U}_{\mathcal{W}}^{l,j}\cdot\Delta_t^{t+\tau}\mathcal{W}^j}_{\textit{cross wage effects}} + \underbrace{\sum_j \mathcal{U}_{\mathcal{Z}}^{l,j}\cdot\Delta_t^{t+\tau}Z^j}_{\textit{pure net supply shift effects}}}_{\textit{net supply shift effects}} ,$$

where $\mathcal{U}_{\mathcal{W}}^{l,j}$ is the (l,j)-element of the Jacobian derivative of $\mathcal{U}_{rigid}$ with respect to the wage rates vector $\mathcal{W}_t$ and $\mathcal{U}_{\mathcal{Z}}^{l,j}$ refers to the corresponding element in the Jacobian derivative with respect to Z_t. Further, $\Delta_t^{t+\tau}\mathcal{W}^l$ is the change in the wage rate in labor market l between times t and $t+\tau$, and $\Delta_t^{t+\tau}Z^l$ is the change in Z_t^l. The first term on the right hand side of the approximation is the change in the unemployment rate in labor market l brought about by changes in the wage rate in this market. The second term accounts for the impacts of changing wages in other labor markets on the unemployment rate in labor market l and the third term incorporates the effects originating from changes in the shift factors. These latter two terms can be interpreted as shifts in the demand and supply curves due to changes in the wage structure and external factors, respectively, and can be summarized as a *net supply shift*, abbreviated as

$$\xi = \underbrace{\sum_{j\neq l}\mathcal{U}_{\mathcal{W}}^{l,j}\cdot\Delta_t^{t+\tau}\mathcal{W}^j + \sum_j \mathcal{U}_{\mathcal{Z}}^{l,j}\cdot\Delta_t^{t+\tau}Z^j}_{\textit{net supply shift effects}}$$

Supposing further that labor supply and demand functions are well-behaved, such that the own-wage derivative $\mathcal{U}_{\mathcal{W}}^{l,l}$ is positive (increases in the wage $\mathcal{W}^l$ *ceteris paribus* lead to higher unemployment), the sign of the net supply shift in period $[t, t+\tau]$ can in most cases be inferred from the observed changes in the unemployment rate $\mathcal{U}^l \equiv \mathcal{U}_{observed}^l$ and the wage rate $\mathcal{W}^l$. Table 1 summarizes these results.

Table 1: Wage and Unemployment Changes, Net Supply Shifts and Immigration

	Decreasing unemployment $\Delta_t^{t+\tau}\mathcal{U}^l < 0$	Constant unemployment $\Delta_t^{t+\tau}\mathcal{U}^l = 0$	Increasing unemployment $\Delta_t^{t+\tau}\mathcal{U}^l > 0$
Increasing wage $\Delta_t^{t+\tau}\mathcal{W}^l > 0$	$\xi < 0$ *weakly adjusting in increasing market (1)*	$\xi < 0$ *strongly adjusting in increasing market (5)*	$\xi = ?$ *strongly rigid (wage push) (2)*
Constant wage $\Delta_t^{t+\tau}\mathcal{W}^l = 0$	$\xi < 0$ *weakly rigid in increasing market (8)*	$\xi = 0$ *stable in stable market (9)*	$\xi > 0$ *weakly rigid in decreasing market (6)*
Decreasing wage $\Delta_t^{t+\tau}\mathcal{W}^l < 0$	$\xi = ?$ *converging (wage pull) (4)*	$\xi > 0$ *strongly adjusting in decreasing market (7)*	$\xi > 0$ *weakly adjusting in decreasing market (3)*

Note: Classification of labor markets according to observed changes in wage and unemployment rates. ξ denotes the net supply shift effect (*i.e.* the sum of cross-wage effects and pure net supply effects). Lightly shaded markets (1,5,8) appear able to integrate immigrants. Unshaded markets (2,3,4,6,7) are less promising for absorbing immigrants. The case 'stable in stable market' (darkly shaded) is undecided.

In markets where unemployment decreases and wages do not fall and in markets where wage increases are not accompanied by rising unemployment, the net supply shift effect ξ is negative (lightly shaded in Table 1). These markets are called 'increasing' as demand grows faster than supply (at a perceived constant wage). Hence, they seem able to absorb an influx of immigrants without creating much socio-political tension and immigration into these labor markets is recommended (*cf.* Bauer, Lofstrom, and Zimmermann, 2000).

On the other hand, markets where unemployment increases and/or wages decrease do not seem very suited to incorporate immigrants. The markets (3), (6) and (7) are characterized by a positive net supply shift ξ (which is equivalent to a negative net demand shift) and are thus 'decreasing' in demand. Also immigration into markets classified as strongly rigid (2) and converging (4) in Table 1 is not recommended, although the sign of the net supply shift is undecided in both cases. In case (2) wages rise, but so is unemployment, indicating a strong rigidity (wage push) in the wage setting process. If immigrants enter as outsiders into these markets their employment chances may be bleak. In case (4) wages fall together with unemployment, indicating a convergence towards competitive wage setting. Since immigration might further increase the downward pressure on wages, immigration into such markets might increase socio-political tension. Finally, in labor markets where neither wages nor unemployment change the net supply shift is zero and no immigration recommendation can be given, case (9) in Table 1.[2] The following section describes how we can estimate $\Delta_t^{t+\tau}\mathcal{W}^l$ and $\Delta_t^{t+\tau}\mathcal{U}^l$ nonparametrically.

3 Nonparametric Estimation

Since any statistical delimitation of labor markets will imply an aggregation of several sub-markets for even more specific skills, no uniform wage is paid in these markets. Hence, within each market l, defined by characteristics $\mathbf{x}_l$, wages vary due to unobserved heterogeneity. The observed wages might also be contaminated with measurement error, which creates additional variance. Therefore, we define the 'wage' $\mathcal{W}_t^l$ in labor market $\mathbf{x}_l$ as the expected value of the wage distribution in this market. Equivalently, the unemployment rate $\mathcal{U}_t^l$ in this labor market can be represented by the expected value of the unemployment status. We thus define

$$\mathcal{W}_t^l \equiv \mathcal{W}_t(\mathbf{x}_l) \equiv E[W_t \mid \mathbf{X} = \mathbf{x}_l]$$

$$\mathcal{U}_t^l \equiv \mathcal{U}_t(\mathbf{x}_l) \equiv E[U_t \mid \mathbf{X} = \mathbf{x}_l],$$

where W_t is the hourly wage rate and U_t is a binary variable indicating whether a person is unemployed at time t. Accordingly, wage and unemployment changes between time t and $t+\tau$ in labor market $\mathbf{x}_l$ are then given by differences in the expected values as:

$$\Delta_t^{t+\tau}\mathcal{W}(\mathbf{x}_l) \equiv E[W_{t+\tau} \mid \mathbf{X} = \mathbf{x}_l] - E[W_t \mid \mathbf{X} = \mathbf{x}_l]$$

$$\Delta_t^{t+\tau}\mathcal{U}(\mathbf{x}_l) \equiv E[U_{t+\tau} \mid \mathbf{X} = \mathbf{x}_l] - E[U_t \mid \mathbf{X} = \mathbf{x}_l].$$

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[2] In case (9), additional competition in these markets may lower wages of residents. It is unclear, though, whether the labor market effects of immigration on residents are significantly large (see the studies cited in the Introduction), nor what the dynamic effects of immigration are. A society open to immigration would probably welcome immigrants to these labor markets, whereas a society less open to immigration may want to prevent immigration in this case.

The traditional (parametric) approach to estimating the expected value of a random variable given a set of characteristics $\mathbf{x}$ (the subscript l is dropped henceforth) proceeds by assuming that the true conditional expectation function can be represented for all feasible $\mathbf{x}$ by a known function, *e.g.* $E[W \mid \mathbf{X} = \mathbf{x}] = \mathbf{x}\boldsymbol{\beta}$ and an unknown but finite coefficient vector $\boldsymbol{\beta}$. Estimating these coefficients $\boldsymbol{\beta}$, for instance by OLS, allows predicting $E[W \mid \mathbf{X} = \mathbf{x}]$ for any labor market $\mathbf{x}$ by $\mathbf{x}\hat{\boldsymbol{\beta}}$. However, these estimates will be biased if the supposed functional form is incorrect, which hardly ever can be ruled out. But not only are the coefficient estimates biased, an inflexible parametric specification can also suppress heterogeneity in the expected wages and unemployment risks among the different labor markets, see Frölich (2001). It may thus appear as if wages and unemployment vary little between different skill groups, since changes can be only due to variations in $\mathbf{x}$ but not in $\boldsymbol{\beta}$. This might pretend similar wage-unemployment developments over time for different labor markets, while they actually might have evolved very differently.

To better allow for heterogeneous (segregated) labor markets it has recently become popular in the empirical labor economics literature to split the population into a few broad labor markets and to estimate expected values by sample means separately in each market. These labor markets are often constructed by discretizing (continuous) variables such as age, experience or education into broad categories, *e.g.* age brackets of 20-29, 30-39, 40-49 years, and partitioning the population into a few cells according to combinations of age group, gender, education, experience, occupation, industry, or region (*cf.* Altonji and Card, 1991; Bound and Johnson, 1992; Card, Kramarz, and Lemieux, 1999; Kahn, 2000; Katz and Murphy, 1992; Krueger and Pischke, 1997; Murphy and Welsh, 1992). However, apart from the obvious loss of information through categorizing continuous regressors, such a nonparametric 'frequency estimator' is generally rather inefficient (Racine and Li, 2000). It neglects the economic links between neighboring age-education cells and does for instance not incorporate into the estimator the well-established stylized fact that wages generally rise with education. Moreover, this analysis delivers results only for very coarsely defined and highly aggregated labor markets, which is unsatisfactory given the highly specialized and sophisticated labor markets found in modern economies. For a more disaggregated examination, however, this approach would not only be inefficient, it is often even infeasible due to the large number of cells. Even with only 10 binary labor market characteristics $2^{10} = 1,024$ different labor markets would need to be analyzed and for some of these labor markets no sample observations might be available, leaving estimates for these markets undefined.[3] This latter problem is exacerbated if the evolution of expected values over time is examined, since this requires that the estimate is defined in all points of time.

Thus, in practice smoothing over the discrete variables is as necessary as smoothing over the continuous variables. We propose estimating expected wages and unemployment risk for specific, narrowly defined labor markets by *nonparametric kernel regression*, using the *hybrid kernel* of Racine and Li (2000) to accommodate discrete as well as continuous variables. Nonparametric regression on a higher-dimensional $\mathbf{x}$ vector is still uncommon in applied econometrics (to our knowledge, the only other studies are Racine and Lee, 2000; Millimet and Racine (2001), and Frölich, 2001), presumably because of the 'curse of dimensionality', *i.e.* the deterioration of the convergence rate of nonparametric estimators with the number of (continuous) regressors (Stone, 1980). However, this does not imply that nonparametric regression is less precise than (misspecified) parametric estimation, once one acknowledges that hardly ever the true form of the conditional expectation function is known. In parametric estimation any bias due to misspecification is tacitly assumed away, whereas the bandwidth selection procedures for nonparametric regression seek to balance variance and squared bias.

Nevertheless, it seems that particularly in higher-dimensional nonparametric regression not only bandwidth selection is of crucial concern but that the choice of the local extrapolation plane is important as well (Frölich, 2001). Whereas conventional Nadaraya (1965) - Watson (1964) kernel regression estimates $E[W \mid \mathbf{X} = \mathbf{x}]$ by the weighted average of the observed wages in labor markets that are similar to $\mathbf{x}$, local linear regression locally fits a linear plane to the data in the neighborhood of $\mathbf{x}$ (*cf.* Fan, 1992; Hastie and Loader, 1992). In this terminology Nadaraya-Watson (local constant) kernel regression can be characterized as fitting locally a 'flat' plane (*i.e.* with slopes zero) to the data. More generally, *local parametric regression*, analyzed by Gozalo and Linton (2000) as a unifying framework for kernel based nonparametric regression methods, fits a parametric model locally in the neighborhood of $\mathbf{x}$, *i.e.* the coefficients $\boldsymbol{\beta}_{\mathbf{x}}$ of the parametric model itself vary with $\mathbf{x}$.[4] In contrast to

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[3] This also makes saturated models, *i.e.* adding the discrete variables in form of fully interacted dummy regressors in a saturated model, as for instance discussed in Angrist (2001), impossible.

[4] Local parametric regression also includes the class of local linear and local polynomial regression, examined in Fan and Gijbels (1996) and Ruppert and Wand (1994).

parametric regression, the specification imposed in local parametric regression is not assumed to be true but rather used to achieve more precise extrapolations around $\mathbf{x}$. Just because data are so sparse in higher-dimensional spaces (*cf.* Härdle, 1991, Ch. 10; Silverman, 1986, p. 94), for many labor markets no or only very few observations will be available in the immediate neighborhood, such that the estimation of $E[W \mid \mathbf{X} = \mathbf{x}]$ must rely on observations that are less nearby.[5]

Local parametric regression also allows incorporating boundedness restrictions on the dependent variable in a natural way. For instance, unemployment status U is a discrete variable taking values in $\{0,1\}$, which could be accommodated by a local logit specification. A local logit specification represents a logit model where the coefficients $\boldsymbol{\beta}_{\mathbf{x}}$ are different for each labor market $\mathbf{x}$, and can be implemented via local likelihood estimation, introduced by Tibshirani and Hastie (1987). Frölich (2001) analyzed the small sample properties of local logit regression with a binary dependent variable. Local logit regression achieved substantial precision gains relative to fully parametric regression in case of misspecification, and it performed only slightly worse in case of correct specification, because larger bandwidth values were chosen by the cross-validation bandwidth selector in the latter case. Nadaraya-Watson kernel regression and local linear regression performed generally much worse.

As an alternative to parametric estimation of the conditional expected value of a binary dependent variable (binary choice model) a variety of semiparametric estimators have been proposed, see *e.g.*

[5] Consider, as a simple example, labor markets characterized by education and gender, and suppose that no (or only very few) observations about highly educated males are available. Nadaraya-Watson regression would estimate the expected wage for highly educated males by a weighted average of the observed wages for less educated male, highly educated female, and less educated female workers. Consequently, the estimated wage for highly educated males would probably be even *lower* than the expected wage for highly educated females. On the other hand, local linear regression would add up the wage premium for education and the gender wage gap in constructing the estimate for highly educated males. In this sense, local linear regression employs locally a monotonic 'additive' extrapolation, and although this linear specification is not fully correct, it still is closer to the true shape of the conditional expectation function and thus leads to more precise extrapolations than the flat approximation of Nadaraya-Watson regression. Thus, if it is conjectured that generally men earn higher wages than women and that higher education commands higher wages, then such (local) monotonicity properties should be incorporated into the estimator, *e.g.* through local linear regression. Indeed, in many economic applications a locally monotonic relationship between the dependent and the explanatory variables seems realistic.

Cosslett (1991), Ichimura (1993), Klein and Spady (1993), or Powell, Stock and Stoker (1989).[6] These semiparametric estimators, however, usually rely on the single-index assumption, that the conditional expectation function can be expressed as a function of a one-dimensional index $\mathbf{x}\boldsymbol{\beta}$, *i.e.* $E[U \mid \mathbf{X}=\mathbf{x}] = g(\mathbf{x}\boldsymbol{\beta})$, where the coefficient vector $\boldsymbol{\beta}$ is global (*i.e.* does not vary with $\mathbf{x}$). This assumption requires that all information contained in $\mathbf{x}$ can be summarized by a one-dimensional number, or in other words, that the heterogeneity between labor markets is essentially one-dimensional. This assumption does not appear plausible in our analysis, which particularly focuses on labor heterogeneity in multiple dimensions. Furthermore, in a comparison between the Klein and Spady estimator and local logit regression in Frölich (2001), the Klein and Spady estimator was unable to detect certain heterogeneity patterns in the data.

Consequently, we estimate expected wages by local linear regression and unemployment risk by local logit. The expected wage for labor market $\mathbf{x}$ in year t is estimated as

$$\hat{E}[W_t \mid \mathbf{X}=\mathbf{x}] = \mathbf{x}\hat{\boldsymbol{\beta}}_{\mathbf{x},t} \qquad \text{with} \qquad \hat{\boldsymbol{\beta}}_{\mathbf{x},t} = \arg\min_{\boldsymbol{\beta}} \sum_{i=1}^{N_t} \left(w_{i,t} - \mathbf{x}_{i,t}\boldsymbol{\beta} \right)^2 \cdot K_{h_{W,t},\lambda_{W,t}} \left(\mathbf{x}_{i,t} - \mathbf{x} \right)$$

and the unemployment probability is estimated by local likelihood as

$$\hat{E}[U_t \mid \mathbf{X}=\mathbf{x}] = \Lambda\left(\mathbf{x}\hat{\boldsymbol{\gamma}}_{\mathbf{x},t} \right) \quad \text{with}$$

$$\hat{\boldsymbol{\gamma}}_{\mathbf{x},t} = \arg\max_{\boldsymbol{\gamma}} \sum_{i=1}^{N_t} \left[u_{i,t} \ln \Lambda\left(\mathbf{x}_{i,t}\boldsymbol{\gamma} \right) + \left(1 - u_{i,t} \right) \ln\left(1 - \Lambda\left(\mathbf{x}_{i,t}\boldsymbol{\gamma} \right) \right) \right] \cdot K_{h_{U,t},\lambda_{U,t}} \left(\mathbf{x}_{i,t} - \mathbf{x} \right),$$

from a sample of observations $\left\{ w_{i,t}, u_{i,t}, \mathbf{x}_{i,t} \right\}_{i=1}^{N_t}$, where $w_{i,t}$ is the wage and $u_{i,t}$ the unemployment status of an individual i attached to the labor market $\mathbf{x}_{i,t}$ (according to his or her characteristics).[7] $\mathbf{x}_{i,t}$ and $\mathbf{x}$ are $1 \times Q$ row vectors with the first element being *one*, K is a multidimensional kernel weighting function that attaches higher weights to observations from labor markets $\mathbf{x}_{i,t}$ which are

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[6] Alternative semiparametric estimators are the M-Score of Manski (1975, 1985) and the smoothed M-Score of Horowitz (1992). These, however, do not attain root-n convergence.

[7] Since wages are observed only for the employed, the estimated wages might be upward biased. However, as we examine *differences* (of expected wages) over time potential biases are likely to cancel out to a large extent. Without an instrumental variable at hand correcting for selectivity is only possible with *ad hoc* functional form assumptions. See also Leung and Yu (1996) or the survey by Puhani (2000) showing that controlling for selection bias is very difficult in practice.

similar to labor market $\mathbf{x}$ and (near) zero weights to observations from labor markets that are very dissimilar to $\mathbf{x}$. $\Lambda(\mathbf{x}\boldsymbol{\gamma}_{\mathbf{x},t}) = e^{\mathbf{x}\boldsymbol{\gamma}_{\mathbf{x},t}} / (1+e^{\mathbf{x}\boldsymbol{\gamma}_{\mathbf{x},t}})$ is the logit function. The coefficients $\hat{\boldsymbol{\beta}}_{\mathbf{x},t}$, $\hat{\boldsymbol{\gamma}}_{\mathbf{x},t}$ are estimated separately for each year *t* from the sample observed in *t*, *i.e.* no time-invariant structures or common effects are assumed. These coefficients $\hat{\boldsymbol{\beta}}_{\mathbf{x},t}$, $\hat{\boldsymbol{\gamma}}_{\mathbf{x},t}$ are different for each labor market $\mathbf{x}$ because of kernel weighting, such that for each labor market separate regressions must be run. However, these coefficients themselves are not of interest and used only for extrapolating the expected wage and unemployment risk to the particular labor market $\mathbf{x}$.

To allow for discrete as well as continuous variables in $\mathbf{x}$ we employ the hybrid kernel function developed by Racine and Li (2000), based on the work of Aitchison and Aitken (1976):

$$K_{h,\lambda}\left(\mathbf{x}_{i,t} - \mathbf{x}\right) = \prod_{q=1}^{q_c} \kappa\left(\frac{x_{q,i,t} - x_q}{h}\right) \cdot \prod_{q=q_c+1}^{Q} \lambda^{1\left(x_{q,i,t} \neq x_q\right)}$$

where it is supposed that the regressors are arranged such that the first q_c regressors $x_{1,i,t}, \ldots, x_{q_c,i,t}$ are continuous variables and the remaining $q_c + 1, \ldots, Q$ regressors are discrete variables (without natural ordering).[8] $K_{h,\lambda}$ is a product kernel that multiplies the separate weight contributions according to each regressor. The multiplicative weight contribution of each continuous variable enters through the univariate kernel function κ and depends on the non-negative bandwidth parameter *h*. We use the compact Epanechnikov kernel with weights declining quadratically to zero, $\kappa(v) = 0.75(1-v^2)\cdot 1(v<1)$. Hence, observations receive lower weights the more dissimilar their characteristics are to the labor market under consideration. Particularly, if at least one of an observation's continuous characteristics differs from labor market $\mathbf{x}$ by more than *h*, this observation receives zero weight and is thus discarded from the estimation. Smoothing over the discrete characteristics is controlled by the bandwidth parameter $\lambda \in [0,1]$. For $\lambda = 1$ the discrete regressors do not affect the kernel weighting, whereas for $\lambda = 0$ an observation can receive only a positive weight if all its discrete characteristics are identical with labor market $\mathbf{x}$. For any λ between 0 and 1 smoothing takes place with respect to the discrete variables and the kernel weight depends on the degree of mismatch between the discrete variables of observation $\mathbf{x}_{i,t}$ and the labor market $\mathbf{x}$. The multiplicative weight contribution of each discrete variable is 1 if it is identical with $\mathbf{x}$, and it is λ if it is different. Hence, the weight contribution according to all discrete regressors is $\lambda^{number\ of\ mismatches}$ and is thus geometrically declining with the number of mismatches. If labor markets were characterized entirely by discrete regressors, a bandwidth value of $\lambda = 0$ would correspond to the 'frequency estimator' mentioned above, where all links between the cells formed by the discrete regressors are neglected.[9] In the other extreme, for $h \to \infty$ and $\lambda = 1$ the kernel weights are identical for each observation (independent of $\mathbf{x}$) and the local linear and the local logit converge to the parametric OLS and logit estimator, respectively. In this sense the linear and the logit model are nested within these nonparametric estimators. Since we use only one bandwidth value h for all continuous variables, these are scaled to the same mean and the same standard deviation to adjust for different measurement scales and to improve numerical accuracy.[10]

Besides taking account of the similarity between $\mathbf{x}_{i,t}$ and $\mathbf{x}$ the kernel function $K_{h,\lambda}\left(\mathbf{x}_{i,t} - \mathbf{x}\right)$ also allows immediately to incorporate a sampling weight due to stratified sampling, as it is the case with the German Socio-Economic Panel, by simply multiplying $K_{h,\lambda}\left(\mathbf{x}_{i,t} - \mathbf{x}\right)$ with the sampling weight of observation *i*.

The bandwidth values h, λ are selected by cross-validation,[11] separately for the wage and for the unemployment risk estimation. The values h, λ are chosen which minimize the average 'one-out-of-sample' squared prediction error

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[8] Discrete variables with natural ordering are not considered as a separate category in this paper. Apart from asymptotic considerations they can essentially be treated like continuous variables in the kernel weighting function. For more details see Racine and Li (2000) or Frölich (2001).

[9] In this case only the constant term in $\boldsymbol{\beta}_{\mathbf{x},t}$, $\boldsymbol{\gamma}_{\mathbf{x},t}$, *i.e.* the sample mean of the respective cell, is identified, since all observations with positive weight have the same characteristics.

[10] Separate bandwidth values for each variable (or groups of variables) could be used, but increase considerably computational burden when bandwidth values are selected by grid search.

[11] For properties of cross-validation bandwidth selection in nonparametric regression see Härdle and Marron (1987), or Racine and Li (2000) for the hybrid kernel. See also Loader (1999) for a recent discussion on bandwidth selection.

$$\left(\hat{h}_{W,t},\hat{\lambda}_{W,t}\right)=\underset{h_{W,t},\lambda_{W,t}}{\arg\min}\sum_{i=1}^{N_t}\left(w_{i,t}-\hat{w}_{-i,t}\right)^2 \qquad \text{and} \qquad \left(\hat{h}_{U,t},\hat{\lambda}_{U,t}\right)=\underset{h_{U,t},\lambda_{U,t}}{\arg\min}\sum_{i=1}^{N_t}\left(u_{i,t}-\hat{u}_{-i,t}\right)^2,$$

where $\hat{w}_{-i,t}$ and $\hat{u}_{-i,t}$ denote the 'leave-one-out' predicted wage and unemployment risk for observation *i*, which are obtained by estimating wage and unemployment at $\mathbf{x}_{i,t}$ from the sample with observation *i* removed. For details on the implementation of the estimators see Frölich (2001).

Following Carroll, Ruppert and Welsh (1998) we compute the variance of the estimated local coefficients $\hat{\boldsymbol{\beta}}_{\mathbf{x},t}$, $\hat{\boldsymbol{\gamma}}_{\mathbf{x},t}$ by the sandwich formula such that the variance of the estimated expected wage for a particular labor market $\mathbf{x}$ is estimated as:

$$\widehat{Var}\left(\hat{E}[W_t \mid \mathbf{X}=\mathbf{x}]\right)=\mathbf{x}\left(\mathbf{X_t'\hat{K}_tX_t}\right)^{-1}\mathbf{X_t'\hat{K}_t\varepsilon_t\varepsilon_t'\hat{K}_tX_t}\left(\mathbf{X_t'\hat{K}_tX_t}\right)^{-1}\mathbf{x}',$$

where $\mathbf{X_t}$ is the matrix of all $\mathbf{x}_{i,t}$, $\mathbf{\hat{K}_t}=diag\left[K_{\hat{h}_{W,t},\hat{\lambda}_{W,t}}\left(\mathbf{x}_{i,t}-\mathbf{x}\right)\right]$ is the diagonal matrix of all kernel weights and $\boldsymbol{\varepsilon}_\mathbf{t}=\mathbf{W_t}-\mathbf{X}_t\hat{\boldsymbol{\beta}}_{\mathbf{x},t}$ is the column vector of all residuals, where $\mathbf{W_t}$ is the vector of all observations $w_{i,t}$. For $\boldsymbol{\varepsilon}_t$ locally homoskedastic this corresponds to the results of Ruppert and Wand (1994) and Fan, *et al.* (1997). Analogously, the variance of the estimated unemployment risk is computed as

$$\widehat{Var}\left(\hat{E}[U_t \mid \mathbf{X}=\mathbf{x}]\right)=G'\mathrm{H}^{-1}\Omega\mathrm{H}^{-1}G \qquad \text{where } G=\frac{e^{\mathbf{x}\hat{\boldsymbol{\gamma}}_{\mathbf{x},t}}}{(1+e^{\mathbf{x}\hat{\boldsymbol{\gamma}}_{\mathbf{x},t}})^2}\mathbf{x}',$$

$$\Omega=\sum_i\left(u_{i,t}-\frac{e^{\mathbf{x}_{i,t}\hat{\boldsymbol{\gamma}}_{\mathbf{x},t}}}{1+e^{\mathbf{x}_{i,t}\hat{\boldsymbol{\gamma}}_{\mathbf{x},t}}}\right)^2\mathbf{x}'_{i,t}\,\mathbf{x}_{i,t}\,K^2_{\hat{h}_{U,t},\hat{\lambda}_{U,t}}\left(\mathbf{x}_{i,t}-\mathbf{x}\right), \quad \mathrm{H}=\sum_i\frac{e^{\mathbf{x}_{i,t}\hat{\boldsymbol{\gamma}}_{\mathbf{x},t}}}{\left(1+e^{\mathbf{x}_{i,t}\hat{\boldsymbol{\gamma}}_{\mathbf{x},t}}\right)^2}\,\mathbf{x}'_{i,t}\,\mathbf{x}_{i,t}\,K_{\hat{h}_{U,t},\hat{\lambda}_{U,t}}\left(\mathbf{x}_{i,t}-\mathbf{x}\right).$$

In the following section, we apply this methodology to the classification of labor markets and corresponding immigration policy recommendations.

4 Results for Western Germany

4.1 Data and Definition of Labor Markets

Our analysis is based on the years 1992 and 1998 of the German Socio-Economic Panel (GSOEP), which is a representative survey of the non-institutionalized German population.[12] In this period the registered unemployment rate increased from 5.9 to 9.3 percent. This rise was accompanied by an increase in the real manufacturing hourly wage rate of about 7.9 percent (International Statistical Yearbook, 2001; OECD, 2000; Statistisches Bundesamt, 2001). Due to the rise in overall unemployment, this period is well suited for the identification of rigid labor markets. Furthermore, labor markets which are identified as 'increasing' in a period of rising unemployment seem particularly able to integrate immigrants without socio-political tensions.

Since no detailed information on the different skills traded in a market is available, we define labor markets through observed characteristics of the individuals supplying their human capital in these markets. Thus, the variables we use to define heterogeneous labor markets are *age* (as a proxy for *experience*)*, years of education, gender, previous occupation, previous sector, previous ownership of employer,* and *region.*[13] Several previous studies have used a subset of these variables to define distinct labor markets (*cf.* Acemoglu, 2001; Altonji and Card, 1991; Borjas, Freeman, and Katz, 1997; Card, Kramarz, and Lemieux, 1999; Card 2001; Fitzenberger, 1999; Krueger and Pischke, 1997; Murphy and Welsh; 1992), but none used all of them. The reason for including previous occupation, sector, and ownership is that these characteristics may approximate employment-specific human capital. '*Previous*' refers to the most recent wave of the last three years at which an occupation, sector, or ownership has been observed. If a person has not been employed in the last three years, he or she is allocated to the category *no work experience*, as this person can be believed to carry not much employment-specific human capital any more. School-leavers are also in this category.

[12] For further information on the GSOEP see http://www.diw-berlin.de/english/sop/index.html.

[13] See Figure B1 in the Appendix for a map of the regions as we define them.

These variables define 127,840 conceivable labor markets $\mathbf{x}$.[14] However, some of these conceivable combinations do not exist as labor markets, *e.g.* the labor market of 18 year old workers with a university degree. Furthermore, only about 12,610 of these combinations are observed in the data set.[15] The following analysis is carried out both for the observed and all conceivable labor markets, whereas the focus will be on the observed ones.

In the local specifications of the mean function ($\mathbf{x}\boldsymbol{\beta}_{\mathbf{x},t}$, $\mathbf{x}\boldsymbol{\gamma}_{\mathbf{x},t}$) the variables *age* and *education* enter linearly whereas *gender, occupation, sector, ownership of employer,* and *region* enter through 11 dummy regressors (a constant is also included; for descriptive statistics see Table A1 in the Appendix). In the kernel weighting function $K\left(\mathbf{x}_{i,t}-\mathbf{x}\right)$ the variables *gender, sector, ownership,* and *region* are treated as unordered discrete variables. *Age*, *education* and *occupation* (coded as *1*=professionals, *2*=clerks, *3*=service workers, *4*=blue-collar workers, *5*=no work experience) are treated as continuous, after being scaled to mean *0* and variance *1*. Although *occupation* is rather an ordered discrete than a continuous variable, treating it as continuous or ordered discrete in the kernel function makes hardly any difference. Including, however, an additional bandwidth parameter for ordered discrete regressors would have increased computational burden substantially. Hence, only two bandwidth values are used (one for the continuous regressors and one for the unordered discrete regressors) and are selected through a grid search over a pre-specified set of 8×8 values for $\left(h,\lambda\right)$: $\{0.50, 0.70, 0.98, 1.37, 1.92, 2.69, 3.77, \infty\}\times\{0.30, 0.40, 0.50, 0.60, 0.70, 0.80, 0.90, 1.00\}$. The bandwidth values {0.98, 1.00} were chosen by cross-validation for the estimation of $\mathcal{W}_{1992}(\mathbf{x})$, {1.37, 0.90} for the estimation of $\mathcal{W}_{1998}(\mathbf{x})$, {1.92, 1.00} for $\mathcal{U}_{1992}(\mathbf{x})$, and {2.69, 0.70} for $\mathcal{U}_{1998}(\mathbf{x})$. With this specification we estimate for each labor market the log wage rate in 1992 and in 1998 and the unemployment probability in 1992 and in 1998.[16] Although the selected bandwidth values appear

[14] 47 age categories (18-64 years old) × 16 education categories × 2 gender categories × 17 combinations of occupation, sector, and ownership of employer × 5 regions.

[15] Either in wave 1992, 1994, 1996 or 1998.

[16] Cross-validation bandwidth selection and estimation for the 12,610 labor markets took about 6 days on a Pentium III processor. We also estimated 2 other specifications: one where age and education were grouped into broad categories and another where four different bandwidth values were employed in the kernel weighting. The former led to a worse fit, whereas the latter produced almost the same results as the main specification. Due to computational burden only a coarse bandwidth grid of 4x4x4x4 values was employed.

large, Table A3 and Figure A1 in the Appendix show that parametric and nonparametric regression lead to different results.

4.2 Classification of Labor Markets

With $\mathcal{W}_{1992}(\mathbf{x})$, $\mathcal{W}_{1998}(\mathbf{x})$, $\mathcal{U}_{1992}(\mathbf{x})$, and $\mathcal{U}_{1998}(\mathbf{x})$ estimated, the labor markets can be classified on the basis of the signs of $\left[\mathcal{W}_{1998}(\mathbf{x})-\mathcal{W}_{1992}(\mathbf{x})\right]$ and $\left[\mathcal{U}_{1998}(\mathbf{x})-\mathcal{U}_{1992}(\mathbf{x})\right]$ according to Table 1. Two-sided t-tests are conducted at the 5 percent level to decide for each labor market whether the wage or unemployment rate have increased, decreased or not changed significantly. This implies a level of 10 percent of the Bonferroni test of the joint null hypothesis $\left[\mathcal{W}_{1998}(\mathbf{x})-\mathcal{W}_{1992}(\mathbf{x})\right]=\left[\mathcal{U}_{1998}(\mathbf{x})-\mathcal{U}_{1992}(\mathbf{x})\right]=0$ (see *e.g.* Mittelhammer, Judge, and Miller, 2000, p. 73f.) and allows a classification of each labor market into one of the nine categories of Table 1. Graphical illustrations of the estimates are given in Figures A1 and B2 to B4 in the Appendix.

A complete report of our estimation results would entail the classification of all 12,610 observed (or all 127,840 conceivable) labor markets. We do not print all the results into this paper. However, at www.siaw.unisg.ch/wagemonitor, the reader can enter the characteristics of a labor market of interest and obtain the corresponding estimation results. Here, we give an overview by reporting the conditional mean (and standard deviation for continuous variables) of the labor market characteristics for each labor market class. Table 2 (observed markets) and Table A2 (all conceivable markets) report the sample equivalent of $E(\mathbf{X}\,|\,\hat{C}=c)$ where C is the variable denoting the labor market classification, which can take on nine different values as defined in Table 1.[17] It should nevertheless be taken into account that these summary statistics cannot genuinely represent the complex heterogeneity of labor markets.

Comparisons of parametric and nonparametric estimates can be found in Figure A1 and Table A3 in the Appendix.

[17] In order to ease the comparison of average labor market characteristics within a classification category c with the average across all labor markets, we report $E(\mathbf{X}\,|\,\hat{C}=c)-E[E(\mathbf{X}\,|\,\hat{C}=c)]$ in Tables B2 to B4 in the Appendix.

As Table 2 shows, the nonparametric estimation results exhibit a distinct picture of different types of labor markets in Western Germany. For about 23 percent of labor markets, significant changes in the wage or unemployment rate can be identified. These markets are classified into the categories (1) to (8) according to Table 1. Looking at the numbers of labor markets in the various groups, category (6) is by far the largest group among the markets which were not 'stable': indeed, more than 15 percent of all observed labor markets experienced unemployment increases due to rigid wages. This finding demonstrates that in a country like Germany, rigidities are relevant for labor market outcomes. Categories (5) and (7) are the next largest groups of labor markets. Together, these labor markets, which displayed perfect wage flexibility during the observation period, comprise about 6 percent of all observed labor markets. The next largest category (3) is the one of labor markets which weakly adjusted to negative net demand shocks by falling wages in the face of rising unemployment. Only 1 percent of all labor markets fall into this category. Even smaller are the numbers of labor markets in categories (2) (strongly rigid, wage push) and (8) (weakly rigid in an increasing market). As to category (2), this means that unemployment is hardly ever created through exogenous real wage push. Rather, wage rigidities seem mainly to occur when there are negative net demand shocks and real wages resist to fall, as is demonstrated by the large numbers of labor markets in category (6). The low number of observations in category (8) shows that the reverse, namely upwardly rigid wages when there is an increase in net demand, is barely observed. This is what one would expect if there are no institutions preventing wages from rising. Instead, the labor markets which enjoyed an increase in net demand are almost completely found in category (3), characterized by rising wages and constant unemployment. Lastly, no labor markets are classified into categories (1) (weakly adjusting in an increasing market) and (4) (converging, wage pull). Given that overall unemployment was low at the beginning of our observation period, it is not surprising that falling unemployment is a rare event. Comparing these results with the classification for all conceivable (not just the observed) labor markets, the shares of the various classification categories are very similar (*cf.* Table A2 in the Appendix). Yet, although the weakly rigid (6) markets are still the largest group, they form a relatively smaller share among all conceivable labor markets. On the other hand, there are more strongly adjusting markets (5) and (7) compared to the observed labor markets. The implications of this labor market classification for immigration policy are discussed in the following section.

Table 2: Mean Characteristics of Labor Markets (Observed Labor Markets Only)

Code	(1) Weakly Adjusting in Incr. M.	(2) Strongly Rigid	(3) Weakly Adjusting in Decr. M.	(4) Con-verging	(5) Strongly Adjusting in Incr. M.	(6) Weakly Rigid in Decr. M.	(7) Strongly Adjusting in Decr. M.	(8) Weakly Rigid in Incr. M.	(9) Stable in Stable Market	All
# Observations	**0**	**26**	**135**	**0**	**347**	**1,932**	**398**	**11**	**9,761**	**12,610**
Age in Years		31.9	30.9		45.2	33.5	36.6	46.8	39.5	38.5
(s.d.)		(10.5)	(4.7)		(10.3)	(9.1)	(10.7)	(9.2)	(11.9)	(11.6)
Education in Years		15.1	10.5		11.3	10.9	13.4	13.5	11.6	11.5
(s.d.)		(3.0)	(2.1)		(3.2)	(1.8)	(3.9)	(3.7)	(2.6)	(2.6)
Gender										
Female		62	44		49	28	30	36	53	48
Previous Occupation										
Professional		0	0		33	1	28	0	22	19
Clerk		0	3		25	4	15	0	28	24
Service Worker		50	73		9	62	19	0	15	23
Blue-Collar Worker		4	19		25	27	25	18	27	27
Previous Sector										
Industry		50	76		34	66	46	0	56	57
Services		4	19		58	29	40	18	36	35
Previous Ownership										
Private Sector		35	92		69	70	60	0	64	65
Public Sector		19	4		24	24	26	18	28	27
No Work Experience		46	4		8	6	14	82	8	8
Region										
Northwestern Germany		12	5		23	12	21	9	19	18
Nordrhein-Westfalen		42	37		19	37	19	9	24	26
Rh.-Hessen-Saar-Pfalz		19	5		31	19	13	9	19	19
Baden-Württemberg		8	48		14	12	32	64	19	19
Bayern		19	4		13	20	15	9	20	19

Note: The table displays $E(\mathbf{X} \mid \hat{C} = c)$ in percent (except for age and education), where C is the variable denoting the labor market classification; shaded labor markets are 'immigration yes' markets; people not employed in the previous three years are not assigned to any occupation, sector, or firm ownership, but to 'no work experience'. S.d.: standard-deviation; Rh.-Hessen-Saar-Pfalz: Rhein-Hessen-Saar-Pfalz. See also Table 1 for the definition of categories (1) to (9).

Source: GSOEP; own calculations.

Table 3: Mean Characteristics of Labor Markets by Their Migration Classification

	Observed Labor Markets Only				All Conceivable Labor Markets			
	Immigration Yes	Immigration No	Immigration Maybe	All	Immigration Yes	Immigration No	Immigration Maybe	All
# Observations	**358**	**2,491**	**9,761**	**12,610**	**7,124**	**15,329**	**105,387**	**127,840**
Age in Years	45.3	33.8	39.5	38.5	44.7	38.2	41.2	41.0
(s.d.)	(10.2)	(9.3)	(11.9)	(11.6)	(14.5)	(13.0)	(13.5)	(13.6)
Education in Years	11.4	11.4	11.6	11.5	12.8	13.0	12.4	12.5
(s.d.)	(3.2)	(2.5)	(2.6)	(2.6)	(3.6)	(3.0)	(3.0)	(3.0)
Gender								
Female	49	29	53	48	57	34	52	50
Previous Occupation								
Professional	32	5	22	19	30	10	25	24
Clerk	24	6	28	24	16	10	26	24
Service Worker	8	56	15	23	12	54	20	24
Blue-Collar Worker	25	26	27	27	33	15	24	24
Previous Sector								
Industry	33	63	56	57	33	64	46	47
Services	57	30	36	35	59	25	50	47
Previous Ownership								
Private Sector	67	69	64	65	44	51	47	47
Public Sector	24	23	28	27	48	38	48	47
No Work Experience	10	8	8	8	8	11	5	6
Region								
Northwestern Germany	23	13	19	18	20	17	20	20
Nordrhein-Westfalen	18	34	24	26	19	22	20	20
Rhein-Hessen-Saar-Pfalz	30	17	19	19	25	19	20	20
Baden-Württemberg	16	17	19	19	14	21	20	20
Bayern	13	18	20	19	22	21	20	20

Note: The table displays $E(\mathbf{X} \mid \hat{C} = c)$ in percent (except for age and education), where C is the variable denoting the labor market classification; people not employed in the previous three years are not assigned to any occupation, sector, or firm ownership, but to 'no work experience'. S.d.: standard-deviation.

Source: GSOEP; own calculations.

4.3 Recommendations for Immigration

Table 3 (and Table B4 in the Appendix) summarize our results with respect to immigration policy. All labor markets classified as (1), (5), or (8) according to Table 1 are considered as being able to absorb immigration ('immigration yes'), whereas immigration into all other markets, except (9), might provoke socio-political tensions ('immigration no'). For labor markets classified as stable in a stable market (9) no recommendation is given ('immigration maybe'). Of the 12,610 observed labor markets 358 (about 3 percent) are identified as suited for immigration, whereas 2,491 (about 20 percent) are classified as 'immigration no' markets. Regarding all conceivable labor markets about 6 percent are classified as 'immigration yes' and 12 percent as 'immigration no'. The remaining markets are classified as 'immigration maybe'.

We consider the observed labor markets first. The characteristics *higher age*, *professional* occupation and *service* sector are over-represented in 'immigration yes' labor markets. Also the region *Rhein-Hessen-Saar-Pfalz* (and *Northwestern Germany*) is over-represented. On the other hand, the occupation *service worker* and *industrial* sector are under-represented, as well as the regions *Nordrhein-Westfalen* and *Bayern*. It may be a surprise to see that *education* is not a distinguishing characteristic between the 'immigration yes' and 'immigration no' markets. Furthermore, the dispersion of *years of education* is large and it is even larger in the 'immigration yes' than the 'immigration no' markets. This suggests there is a group of labor markets for highly educated professionals which can take in immigrants, but there is also scope for immigration in some low-education markets.

The 'immigration no' labor markets tend to be characterized by below-average *age*, an over-representation of *males*, *service workers*, the *industry* sector, and the (staple-industry) region of *Nordrhein-Westfalen*. On the other hand, *professionals* and *clerks* as well as the *services* sector are under-represented. Notice that these labor markets are largely characterized by downward wage-rigidities, since most of the 'immigration no' markets are classified as 'weakly rigid in a decreasing market' (6) (see Table 2) meaning that wages did not fall in the face of negative net demand shocks. This finding that wage rigidities are affecting young workers particularly is consistent with Kahn's (2000) results, although those are based on a different data source, which mainly uses cross-sectional information for a range of industrialized countries (including Germany). The over-representation of the *industry* sector and of *Nordrhein-Westfalen* comes as expected, knowing the powerful union influence in these areas. An interesting aspect, however, is that, although 72 percent of rigid labor markets are for *males* and 66 percent are in the *industry* sector, only around 27 percent share the characteristic *blue-collar* worker, as opposed to 62 percent for *service workers*. Hence, wage rigidities seem not to be a distinguishing characteristic of labor markets for *industrial*, *blue-collar* or *low education* workers, but rather for *service workers* in the *industry sector*. Examining also columns (2) and (3) in Table 2, it seems that *service workers* and the *industry sector* are particularly affected by rising unemployment, and that only few adjust their wages to this development. What might sound paradoxical is in fact plausible due to the trait of the German collective bargaining system that all tariff-paid workers in an industry are paid according to the industry tariff (*cf.* Fitzenberger and Franz, 1999). Hence service workers with similar qualifications earn different wages in different industries.

The second largest category among the markets with 'immigration no' recommendation is 'strongly adjusting in a decreasing market' (7). In these markets, unemployment does not change, but wages fall due to a negative net demand shock. Interestingly, these flexible (in terms of real wages) labor markets are distinguished from the 'weakly rigid in a decreasing market' (6) labor markets in that they display an over-representation of the characteristics *professional*, people with *no work experience*, *service* sector, and the region of *Baden-Württemberg*. These are groups less covered by unions. Furthermore, unions often orient their wage policy to developments in prosperous *Baden-Württemberg.* The evidence is therefore consistent with the view that unions may be responsible for wage rigidities, although no causal effect can be identified here. The third largest category of 'immigration no' labor markets is 'weakly adjusting in a decreasing market' (3). The average characteristics of this subset are very similar to those for 'weakly rigid in a decreasing market' (6) labor markets, although the over-representation of *young age*, *service workers*, *private industrial* sector, and *Baden-Württemberg* is even more pronounced. Lastly, the few 'strongly rigid' (2) labor markets exhibit an over-representation of *young, highly educated, female, no work experience, service* workers, and the region *Nordrhein-Westfalen*. This evidence is consistent with the view that pay scales for labor market entrants, which are usually agreed upon by collective bargaining, may be inefficient in that they create unemployment.

Table 3 (and Table B4 in the Appendix) provide the classification results for all 127,840 conceivable labor markets. The broad results concerning the average characteristics in the different classes are unchanged. A difference is that *blue-collar* workers (and *females*) are over-represented in the 'immigration yes' markets. The region *Northwestern Germany* is not over-represented any more and instead of *Nordrhein-Westfalen* and *Bayern*, *Baden-Württemberg* is now under-represented. Moreover, in the 'immigration no' labor markets, those with *no work experience* are now over-represented.

However, it should always be kept in mind that these broad summary statistics are only to a limited extent informative about the substantial heterogeneity between labor markets. To fully appreciate the richness of the nonparametric results, we invite the reader to visit www.siaw.unisg.ch/wagemonitor.

5 Conclusions

This paper has classified west German labor markets according to their potential for integrating immigrants. The basic premise of the classification is that labor markets facing falling wages and/or rising unemployment may create socio-political tensions in face of immigration. On the other hand, labor markets with rising wage rates should be able to integrate immigrants. We have developed a theoretical framework and classified labor markets according to their recent wage and unemployment developments, which have been estimated nonparametrically for each labor market.

To sum up, 'immigration yes' labor markets are characterized by above-average shares of *experienced, professional,* and *service sector* labor. The main region over-represented in these markets is *Rhein-Hessen-Saar-Pfalz*. 'Immigration no' labor markets, on the other hand, often exhibit below-average *age*, and an over-representation of *males*, occupation as *service workers*, the *industry sector*, and the state of *Nordrhein-Westfalen*. These results comply with the current German government's view that highly qualified people should be preferred for immigration. However, there may be a trade-off between accepting experienced workers as immigrants and the wish to take in young people in order to bolster future payments into Germany's ailing social security system. These aggregated results, however, do not necessarily imply conflicting aims, since the heterogeneity of labor markets is very large, as the large standard deviations for age in the different labor market categories show. Hence, there are labor markets for both low age and for high age workers which are suited for immigration. Looking at means only does not do justice to the ample heterogeneity found between the labor markets in a modern economy. Hence, analysis of heterogeneity, *e.g.* through nonparametric regression as carried out in this paper, deserves more attention than it often receives.

In our view, a permanent tracking of labor markets at a detailed level by a method as presented in this paper can serve as a useful information tool to monitor immigration policies. The developed methodology has certain advantages over a point system which assigns a *fixed* number of 'immigration points' for certain characteristics. Unlike the point system, our nonparametric analysis allows the 'immigration virtue' of a certain trait (*e.g.* experience) to *vary* between different labor markets. It should be stressed that our approach is not less transparent than the point system, as the immigration recommendations can be disseminated to policy makers as well as potential immigrants through the internet.

Furthermore, we have demonstrated that the large majority of the 'immigration no' markets are facing real wage rigidities. This empirical result substantiates the importance of taking wage rigidities into account when formulating immigration policies in European countries. Furthermore, because we find regional differences in the 'immigration aptitude' of labor markets, we argue that immigration does not have to be regulated at the federal level. States or regions may well decide whether they want temporary immigration or not. Such a decentralized approach to immigration would probably require a temporary regional residence permit for immigrants, similar to the one of Switzerland, for example.

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Appendix A

Table A1: Descriptive Statistics

Variable	Sample Means (in Percent)				Unemployment Rates (in Percent) in Subpopulations			
	Wage Sample		Unemployment Sample					
	1992	**1998**	**1992**	**1998**	**1992**	**1994**	**1996**	**1998**
Hourly Wage or Sample Unemployment Rate, resp.	21	25	4	7	4	6	6	7
(s.d.)	(12)	(14)	-	-	-	-	-	-
Age in Years								
16-25	15	9	14	10	4	11	13	16
26-35	29	33	28	31	4	6	6	6
36-45	26	26	26	27	4	4	5	9
46-55	22	23	22	23	3	5	5	4
56-65	8	10	9	9	3	2	4	4
Education in Years								
0-8	4	5	4	5	7	7	14	10
9	11	8	12	9	5	7	8	11
10-11	57	53	57	52	4	6	5	7
12-13	10	15	10	14	6	4	6	6
14	5	6	5	6	2	3	5	3
15-20	13	14	13	14	2	5	7	6
Gender								
Female	42	42	44	43	5	5	7	7
Male	58	58	56	57	3	6	5	7
Previous Occupation								
Professional	20	22	19	21	1	3	3	2
Clerk	22	24	20	21	2	4	4	3
Service Worker	20	19	21	21	2	3	3	9
Blue-Collar	35	33	34	31	2	6	5	5
No Work Experience	3	3	6	6	39	27	33	44

Table A1: Descriptive Statistics (continued)

Variable	Sample Means (in Percent)				Unemployment Rates (in Percent) in Subpopulations			
	Wage Sample		Unemployment Sample					
	1992	1998	1992	1998	1992	1994	1996	1998
Previous Sector								
Industry	43	41	42	39	2	5	4	5
Services	54	56	53	56	1	4	4	5
No Work Experience	3	3	6	6	39	27	33	44
Previous Ownership								
Public Sector	26	27	24	24	1	3	4	2
Private Sector	71	71	70	70	2	5	4	6
No Work Experience	3	3	6	6	39	27	33	44
Region								
Northwestern Germany	19	20	19	20	4	5	6	6
Nordrhein-Westfalen	27	29	29	30	5	6	6	9
Rhein-Hessen-Saar-Pfalz	17	15	16	15	3	6	6	6
Baden-Württemberg	18	18	17	17	3	5	6	5
Bayern	19	18	19	17	2	6	6	8
# Observations	4,203	4,066	5,179	4,976	5,179	4,924	5,402	4,976

Notes: All figures are weighted by the GSOEP sample weights. Means and unemployment rates are given in percent, except for the wage rate. The real hourly wage rate is measured in 1998 Deutsche Marks. The 1992 wages are adjusted by the consumer price index for western Germany (Statistisches Bundesamt, 2000).

The variables *occupation*, *sector*, and *ownership* are taken from the most recently available of the corresponding three previous waves. People with *no work experience* conceptually build an extra category for each of these three dummy variable groups. Hence this variable is reported three times here, although it only appears once in the estimation.

Source: GSOEP; own calculations.

Table A2: Mean Characteristics of Labor Markets by Their Classification (All Conceivable Labor Markets)

	(1) Weakly Adjusting in Incr. M.	(2) Strongly Rigid	(3) Weakly Adjusting in Decr. M.	(4) Con-verging	(5) Strongly Adjusting in Incr. M.	(6) Weakly Rigid in Decr. M.	(7) Strongly Adjusting in Decr. M.	(8) Weakly Rigid in Incr. M.	(9) Stable in Stable Market	All
# Observations	**78**	**379**	**434**	**187**	**6,748**	**8,056**	**6,273**	**298**	**105,387**	**127,840**
Age in Years	45.7	28.2	33.9	52.7	44.5	34.3	43.6	50.3	41.2	41.0
(s.d.)	(16.0)	(11.8)	(7.7)	(5.8)	(14.7)	(9.3)	(15.0)	(8.1)	(13.5)	(13.6)
Education in Years	16.3	14.8	11.6	16.0	12.7	12.0	14.2	15.5	12.4	12.5
(s.d.)	(1.6)	(2.2)	(3.1)	(1.7)	(3.6)	(2.3)	(3.2)	(2.4)	(3.0)	(3.0)
Gender										
Female	45	33	39	34	58	33	36	33	52	50
Previous Occupation										
Professional	0	0	0	0	32	1	22	0	25	24
Clerk	0	0	4	0	17	7	14	0	26	24
Service Worker	1	61	82	3	13	76	25	5	20	24
Blue-Collar Worker	40	1	8	19	34	10	24	16	24	24
Previous Sector	59	38	7	79	5	6	15	80	5	6
Industry										
Services	0	61	81	2	35	78	46	0	46	47
Previous Ownership	41	1	12	19	61	16	39	21	50	47
Private Sector										
Public Sector	0	21	86	2	46	53	49	1	47	47
No Work Experience	41	41	7	20	49	41	36	20	48	47
Region										
Northwestern	28	13	13	9	19	13	24	27	20	20
Nordrhein-Westfalen	12	28	36	18	20	28	14	8	20	20
Rh.-Hessen-Saar-	4	14	13	9	26	20	19	9	20	20
Baden-Württemberg	51	13	30	63	12	15	26	50	20	20
Bayern	5	31	8	1	22	25	17	5	20	20

Note: The table displays $E(\mathbf{X} \mid \hat{C} = c)$ in percent (except for age and education), where C is the variable denoting the labor market classification; shaded labor markets are 'immigration yes' markets; people not employed in the previous three years are not assigned to any occupation, sector, or firm ownership, but to 'no work experience'. S.d.: standard-deviation; Rh.-Hessen-Saar-Pfalz: Rhein-Hessen-Saar-Pfalz.

Source: GSOEP; own calculations.

Table A3 a: Numbers of Labor Markets Classified into Categories by Nonparametric and Parametric Regression

Nonparametric Classification \ Parametric Classification	(2)	(3)	(5)	(6)	(7)	(8)	(9)	All
(2) Strongly Rigid	**0**	0	0	14	0	0	12	**26**
(3) Weakly Adjusting in a Decr. Mkt.	0	**2**	0	112	0	0	21	**135**
(5) Strongly Adjusting in an Incr. Mkt.	0	0	**59**	10	0	0	278	**347**
(6) Weakly Rigid in a Decr. Mkt.	0	33	0	**1,681**	0	0	218	**1,932**
(7) Strongly Adjusting in a Decr. Mkt.	0	5	1	32	**15**	0	345	**398**
(8) Weakly Rigid in an Incr. Mkt.	0	0	0	0	0	**0**	11	**11**
(9) Stable in a Stable Market	26	10	698	949	38	11	**8,029**	**9,761**
All	**26**	**50**	**758**	**2,798**	**53**	**11**	**8,914**	**12,610**

Table A3 b: Labor Markets Classified into Category by Nonparametric Regression in Percent of Labor Markets Classified into Category by Parametric Regression

Nonparametric Classification \ Parametric Classification	(2)	(3)	(5)	(6)	(7)	(8)	(9)	All
(2) Strongly Rigid	**0**	0	0	1	0	0	0	**0**
(3) Weakly Adjusting in a Decr. Mkt.	0	**4**	0	4	0	0	0	**1**
(5) Strongly Adjusting in an Incr. Mkt.	0	0	**8**	0	0	0	3	**3**
(6) Weakly Rigid in a Decr. Mkt.	0	66	0	**60**	0	0	2	**15**
(7) Strongly Adjusting in a Decr. Mkt.	0	10	0	1	**28**	0	4	**3**
(8) Weakly Rigid in an Incr. Mkt.	0	0	0	0	0	**0**	0	**0**
(9) Stable in a Stable Market	100	20	92	34	72	100	**90**	**77**
All	100	100	100	100	100	100	100	**100**

Note: The table considers observed labor markets only. To illustrate, the bold number 60 in Table A3b means that 60 percent of labor markets classified into category (6) by parametric regression are also classified into this category by nonparametric regression.
Source: GSOEP; own calculations.

Figure A1 compares the nonparametric regression results to the results that would have been obtained when using parametric regression, *i.e.* it compares the local parametric regression results with bandwidths selected by cross-validation to a regression with infinite bandwidth values $\left(h = \infty, \lambda = 1\right)$. Although the selected bandwidth values appear large, differences between the parametric and the nonparametric regression are still substantial, as can be seen from Figure A1, where predicted log wage and unemployment rate changes according to nonparametric and parametric regression are plotted against each other.

As a measure of the precision gain through using nonparametric instead of parametric regression we compare the *average squared out-of-sample prediction error* in form of the leave-one-out cross-validation criterion. Whereas the average squared prediction error with respect to the estimation of the log-wage in 1992 (1998) is 0.148 (0.158) for nonparametric regression, it is 0.168 (0.183) with parametric regression. This shows a clear precision gain through nonparametric regression. The precision gains for the estimation of the unemployment risks are smaller. The average squared prediction error is 0.034 (0.058) for 1992 (1998) for local logit and 0.035 (0.059) for parametric logit.

Table A3 compares the labor market classifications according to parametric and nonparametric regression. Again it is demonstrated that the outcomes from the more flexible nonparametric estimation differ from the ones of the parametric model.

Figure A1 a: Scatter Plot of Estimated Wage Rate Changes by the Parametric (Abscissa) and the Non-Parametric Models (Ordinate)

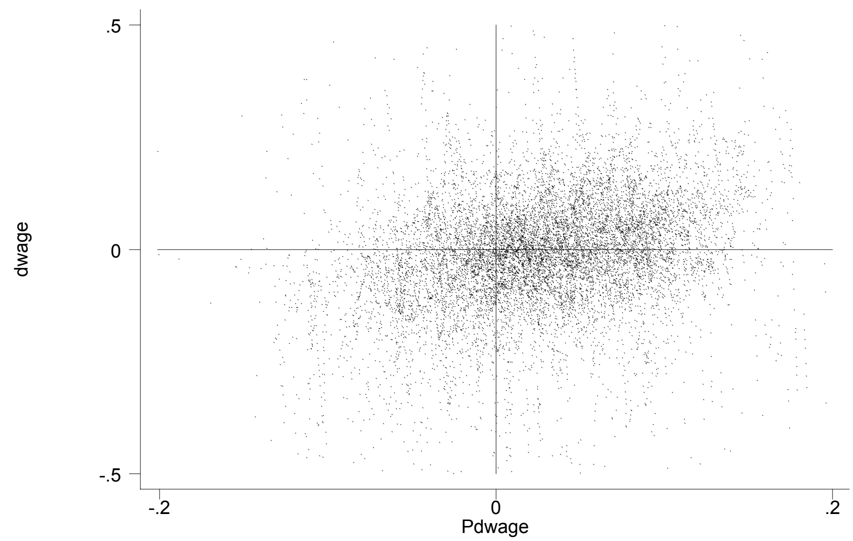
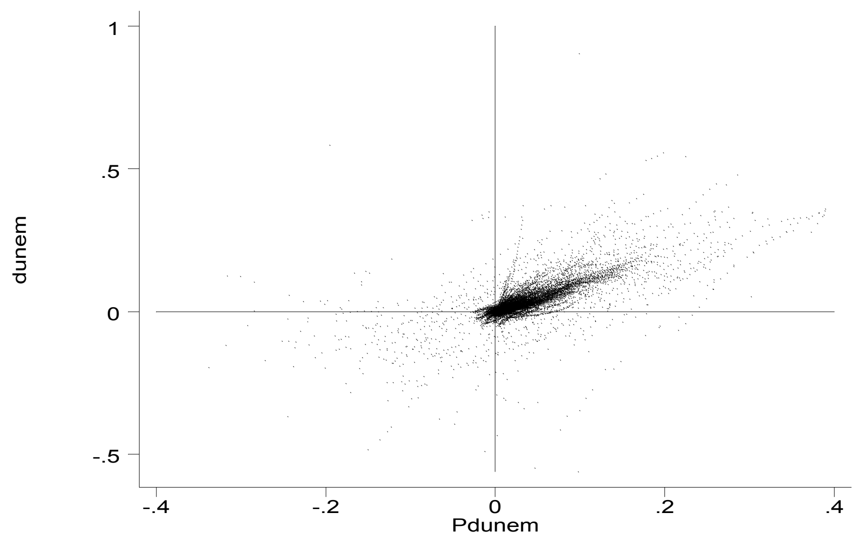


Figure A1 b: Scatter Plot of Estimated Unemployment Rate Changes by the Parametric (Abscissa) and the Non-Parametric Models (Ordinate)



Note: Observed labor markets only. In Figure A1 a, about 1.5 percent of observations are not displayed. These are outliers with estimated absolute log-wage changes larger than 0.5. Only 1.2 percent of all labor markets exhibit a point estimate for the log-wage change larger than 0.5 in absolute value which is significantly different from zero.

Source: GSOEP; own calculations.

Appendix B

Table B1: Selection of Sample

# Observations	Year	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Labor Force	**1992**	9080	5788	5765	5526	5398	5231	**5186**
	1998	10480	6458	6423	5374	5271	5054	**4983**
Employed	**1992**	5517	4632	4621	4446	4360	4243	**4206**
	1998	6007	5105	5087	4370	4303	4120	**4069**

Note: For our analysis we used the waves 1992 and 1998 of the German Socio-Economic Panel and dropped individuals with missing or inconsistent information on relevant characteristics. In 1992 a labor force status was reported for 9080 observations, of which 5517 were employed. In 1998 these figures were 10480 and 6007, respectively, see column (1). The following columns provide the number of observations retained after eliminating successively: individuals out of the labor force and employed individuals without a reported hourly wage (2); observations with age below 16 or above 65 years (3); individuals who were not observed in any of the three previous waves (see the discussion in Section 4.1) (4); observations with missing information on occupation, sector or firm ownership (5); observations occupied in agriculture or in managerial functions (6); observations with missing information on other variables used in the estimation (7). We retain 5186 (4983) observations in 1992 (1998) as the basis for the nonparametric regression, of which 4206 (4069) were employed with reported wage rate.

When generating all combinations of characteristics for the analysis of all conceivable labor markets, we use only the age interval from 18 to 64 years, since only very few 16, 17 or 65 year olds are observed in the (active) labor force. For instance, of the about 5000 observations in column (7) only 7 were 16, 17, or 65 years old. (Nevertheless, in the analysis for the observed labor markets, these observations are still retained.)

Source: German Socio-Economic Panel (GSOEP); own calculations.

Table B2: Mean Characteristics of Labor Markets by Their Classification Less Mean Characteristics of All Labor Markets (Observed Labor Markets only)

Code	(1) Weakly Adjusting in Incr. M.	(2) Strongly Rigid	(3) Weakly Adjusting in Decr. M.	(4) Con-verging	(5) Strongly Adjusting in Incr. M.	(6) Weakly Rigid in Decr. M.	(7) Strongly Adjusting in Decr. M.	(8) Weakly Rigid in Incr. M.	(9) Stable in Stable Market	All
# Observations	**0**	**26**	**135**	**0**	**347**	**1,932**	**398**	**11**	**9,761**	**12,610**
Age in Years		-6.7	-7.6		6.7	-5.1	-1.9	8.3	1.0	0.0
(s.d.)		-(1.2)	-(6.9)		-(1.4)	-(2.5)	-(1.0)	-(2.4)	(0.2)	(0.0)
Education in Years		3.5	-1.0		-0.2	-0.6	1.9	1.9	0.1	0.0
(s.d.)		(0.4)	-(0.4)		(0.6)	-(0.8)	(1.3)	(1.1)	(0.0)	(0.0)
Gender										
Female		14	-4		1	-20	-18	-12	5	0
Previous Occupation										
Professional		-19	-19		15	-18	9	-19	3	0
Clerk		-24	-21		1	-20	-9	-24	5	0
Service Worker		27	51		-14	40	-4	-23	-8	0
Blue-Collar Worker		-23	-8		-2	0	-2	-9	0	0
Previous Sector										
Industry		-7	19		-23	9	-11	-57	-1	0
Services		-31	-16		23	-7	5	-17	1	0
Previous Ownership										
Private Sector		-31	27		3	4	-5	-65	-1	0
Public Sector		-8	-23		-3	-2	-1	-9	1	0
No Work Experience		38	-3		0	-2	6	74	0	0
Region										
Northwestern Germany		-6	-13		5	-6	3	-9	1	0
Nordrhein-Westfalen		16	11		-7	11	-7	-17	-2	0
Rh.-Hessen-Saar-Pfalz		1	-13		12	1	-6	-10	0	0
Baden-Württemberg		-11	30		-4	-7	14	45	0	0
Bayern		0	-15		-6	1	-4	-10	1	0

Note: The table displays $E(\mathbf{X} \mid \hat{C}=c)-E[E(\mathbf{X} \mid \hat{C}=c)]$ in percent (except for age and education), where C is the variable denoting the labor market classification; shaded labor markets are 'immigration yes' markets; people not employed in the previous three years are not assigned to any occupation, sector, or firm ownership, but to 'no work experience'. Rh.-Hessen-Saar-Pfalz: Rhein-Hessen-Saar-Pfalz.

Source: GSOEP; own calculations.

Table B3: Mean Characteristics of Labor Markets by Their Classification Less Mean Characteristics of All Labor Markets (All Conceivable Labor Markets)

Code	(1) Weakly Adjusting in Incr. M.	(2) Strongly Rigid	(3) Weakly Adjusting in Decr. M.	(4) Con-verging	(5) Strongly Adjusting in Incr. M.	(6) Weakly Rigid in Decr. M.	(7) Strongly Adjusting in Decr. M.	(8) Weakly Rigid in Incr. M.	(9) Stable in Stable Market	All
# Observations	**78**	**379**	**434**	**187**	**6,748**	**8,056**	**6,273**	**298**	**105,387**	**127,840**
Age in Years	4.7	-12.8	-7.1	11.7	3.5	-6.7	2.6	9.3	0.2	0.0
(s.d.)	(2.4)	-(1.8)	-(5.9)	-(7.8)	(1.1)	-(4.3)	(1.5)	-(5.5)	-(0.1)	(0.0)
Education in Years	3.8	2.3	-1.0	3.5	0.2	-0.6	1.7	2.9	-0.1	0.0
(s.d.)	-(1.5)	-(0.9)	(0.1)	-(1.4)	(0.5)	-(0.7)	(0.2)	-(0.7)	(0.0)	(0.0)
Gender										
Female	-5	-17	-11	-16	8	-17	-14	-17	2	0
Previous Occupation										
Professional	-24	-24	-24	-24	8	-22	-1	-24	2	0
Clerk	-24	-24	-20	-24	-6	-16	-9	-24	3	0
Service Worker	-22	37	58	-21	-11	52	2	-19	-4	0
Blue-Collar Worker	16	-22	-16	-5	10	-14	0	-8	1	0
Previous Sector										
Industry	-47	14	34	-45	-13	31	-1	-47	-2	0
Services	-6	-46	-35	-28	14	-31	-8	-27	2	0
Previous Ownership										
Private Sector	-47	-26	39	-46	-1	6	2	-46	0	0
Public Sector	-6	-6	-40	-27	2	-6	-11	-27	1	0
No Work Experience	53	32	1	73	-1	0	9	74	-1	0
Region										
Northwestern	8	-7	-7	-11	-1	-8	4	7	0	0
Nordrhein-Westfalen	-9	8	16	-2	0	8	-7	-12	0	0
Rh.-Hessen-Saar-	8	-6	-7	-11	6	0	-2	-11	0	0
Baden-Württemberg	31	-7	10	43	-8	-5	6	30	0	0
Bayern	-15	11	-12	-19	2	5	-3	-15	0	0

Note: The table displays $E(\mathbf{X} \mid \hat{C}=c) - E[E(\mathbf{X} \mid \hat{C}=c)]$ in percent except for age and education, where C is the variable denoting the labor market classification; shaded labor markets are 'immigration yes' markets; people not employed in the previous three years are not assigned to any occupation, sector, or firm ownership, but to 'no work experience'; Rh.-Hessen-Saar-Pfalz: Rhein-Hessen-Saar-Pfalz.

Source: GSOEP; own calculations.

Table B4: Mean Characteristics of Labor Markets by Their Migration Classification Less Mean Characteristics of All Labor Markets

	Observed Labor Markets Only				All Conceivable Labor Markets			
Code	**Immigration Yes**	**Immigration No**	**Immigration Maybe**	**All**	**Immigration Yes**	**Immigration No**	**Immigration Maybe**	**All**
# Observations	**358**	**2,491**	**9,761**	**12,610**	**7,124**	**15,329**	**105,387**	**127,840**
Age in Years	6.7	-4.7	1.0	0.0	3.7	-2.8	0.2	0.0
(s.d.)	-(1.4)	-(2.3)	(0.2)	(0.0)	(0.9)	-(0.6)	-(0.1)	(0.0)
Education in Years	-0.2	-0.2	0.1	0.0	0.3	0.5	-0.1	0.0
(s.d.)	(0.7)	-(0.1)	(0.0)	(0.0)	(0.5)	-(0.1)	(0.0)	(0.0)
Gender								
Female	1	-19	5	0	7	-16	2	0
Previous Occupation								
Professional	14	-13	3	0	6	-14	2	0
Clerk	1	-18	5	0	-7	-14	3	0
Service Worker	-14	33	-8	0	-12	30	-4	0
Blue-Collar Worker	-2	-1	0	0	10	-8	1	0
Previous Sector								
Industry	-24	6	-1	0	-14	17	-2	0
Services	22	-6	1	0	12	-22	2	0
Previous Ownership								
Private Sector	1	4	-1	0	-3	4	0	0
Public Sector	-3	-3	1	0	1	-9	1	0
No Work Experience	2	0	0	0	3	6	-1	0
Region								
Northwestern Germany	5	-5	1	0	0	-3	0	0
Nordrhein-Westfalen	-8	9	-2	0	-1	2	0	0
Rhein-Hessen-Saar-Pfalz	11	-1	0	0	5	-3	0	0
Baden-Württemberg	-3	-1	0	0	-6	1	0	0
Bayern	-6	-1	1	0	2	1	0	0

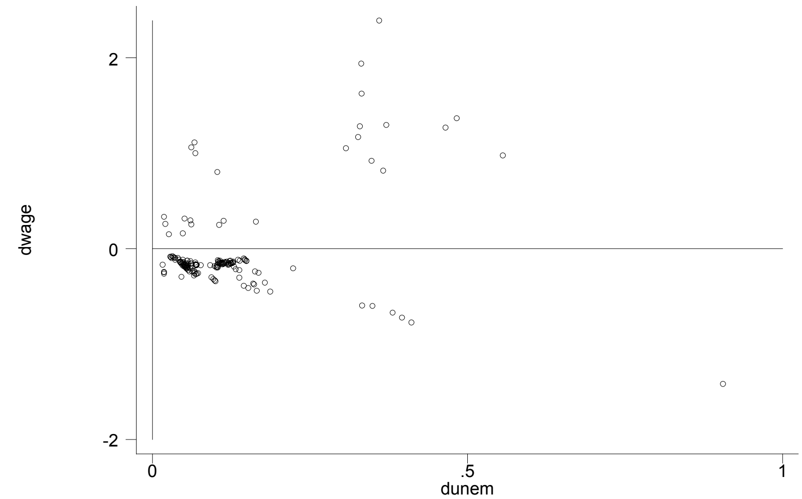
Note: The table displays $E(\mathbf{X} \mid \hat{C}=c) - E[E(\mathbf{X} \mid \hat{C}=c)]$ in percent except for age and education, where C is the variable denoting the labor market classification; people not employed in the previous three years are not assigned to any occupation, sector, or firm ownership, but to 'no work experience'.

Source: GSOEP; own calculations.

Figure B1: Definition of West German Regions

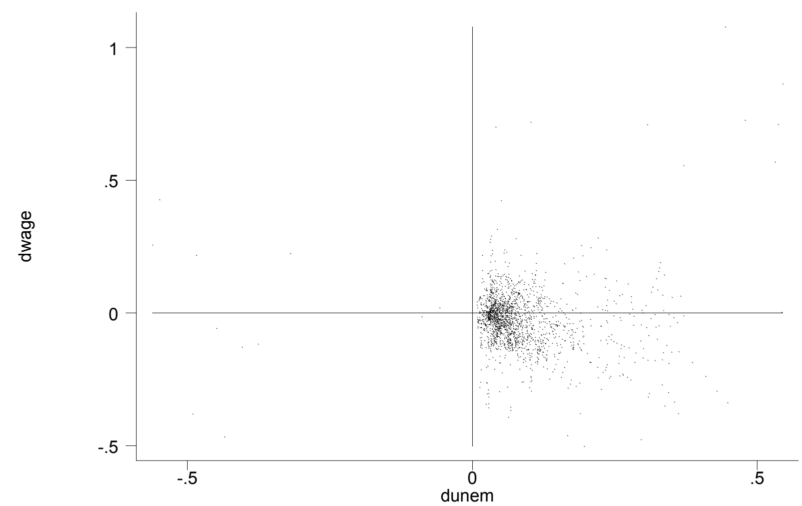
Note: *Northwestern Germany* comprises the federal states Schleswig-Holstein, Hamburg, Bremen, and Niedersachsen. *Rhein-Hessen-Saar-Pfalz* comprises the federal states of Rheinland-Pfalz, Hessen, and Saarland. *Nordrhein-Westfalen*, *Baden-Württemberg*, and *Bayern* are each a single federal state.

Figure B2 a: Graphical Illustration of Labor Markets with both Significant Wage and Unemployment Change (Observed Labor Markets Only)



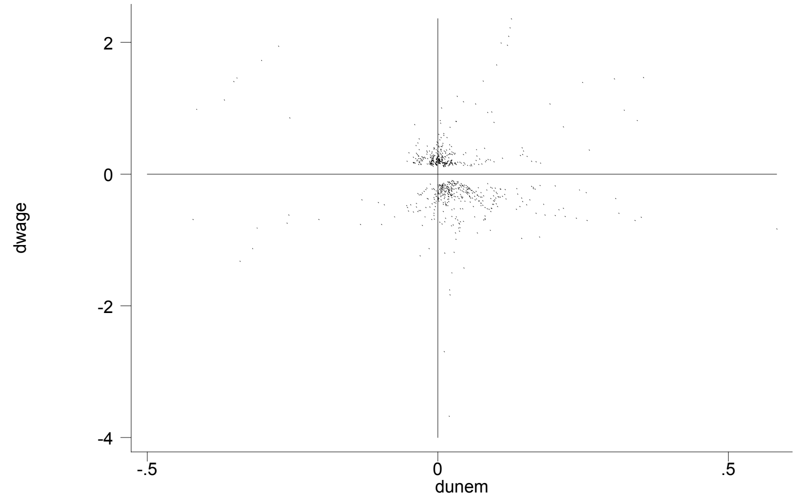
Note: dwage is the estimated change in the logarithm of the wage rate, *dunem* is the estimated change in the unemployment rate. According to Table 1, labor markets in the the upper right are classified as ‘strongly rigid’ (2); those in the lower right as ‘weakly adjusting in a decreasing market’ There are no observed labor markets in categories (1) (‘weakly adjusting in an increasing market’) and (4) (‘converging’). Note that only 1.2 percent of all labor markets exhibit a point estimate for the log-wage change larger than 0.5 in absolute value which is significantly different from zero.

Figure B2 b: Graphical Illustration of Labor Markets with Insignificant Wage but Significant Unemployment Change (Observed Labor Markets Only)



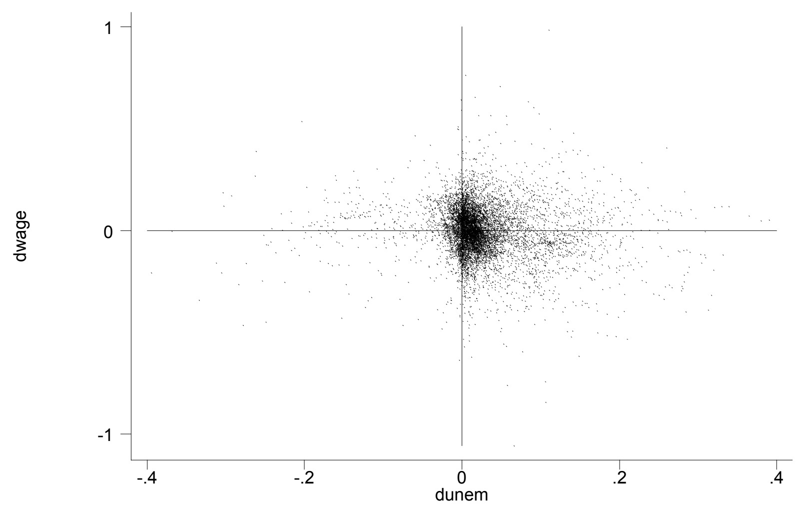
Note: Labor markets to the right of the vertical line are classified as ‘weakly rigid in a decreasing market’ (6), labor markets to the left of the vertical line as ‘weakly rigid in an increasing market’ (8).

Figure B2 c: Graphical Illustration of Labor Markets with Significant Wage but Insignificant Unemployment Change (Observed Labor Markets Only)



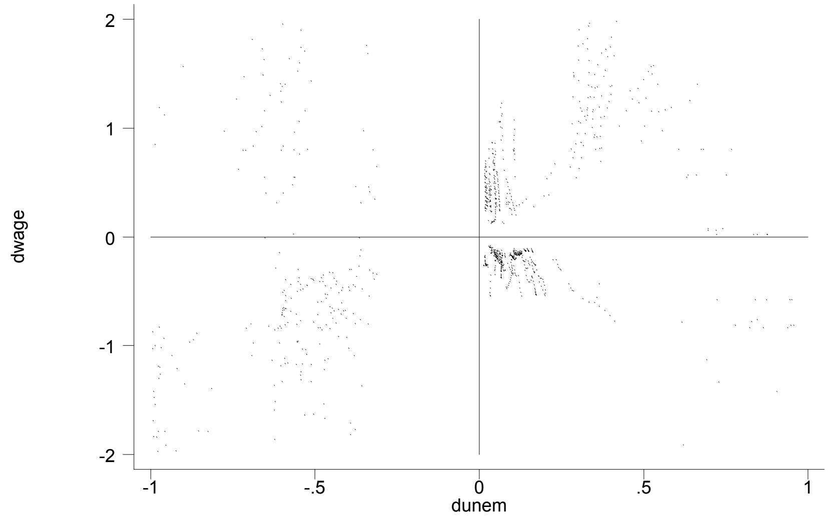
Note: Labor markets above the horizontal line are classified as 'strongly adjusting in an increasing market' (5), labor markets below the line as 'strongly adjusting in a decreasing market' (7). Note that only 1.2 percent of all labor markets exhibit a point estimate for the log-wage change larger than 0.5 in absolute value which is significantly different from zero.

Figure B2 d: Graphical Illustration of Labor Markets with both Insignificant Wage and Unemployment Change (Observed Labor Markets Only)



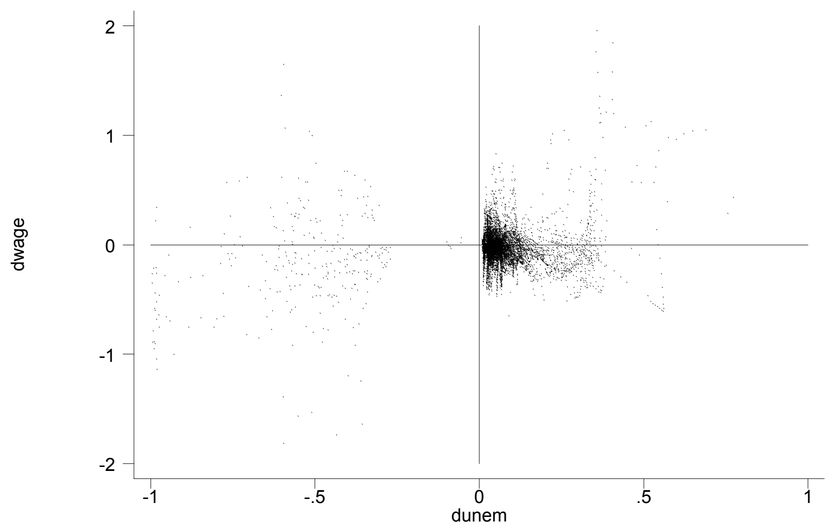
Note: dwage is the estimated change in the logarithm of the wage rate, *dunem* is the estimated change in the unemployment rate. All labor markets displayed are classified as 'stable in a stable market' (9).
Source: GSOEP; own calculations.

Figure B3 a: Graphical Illustration of Labor Markets with both Significant Wage and Unemployment Change (All Conceivable Labor Markets)



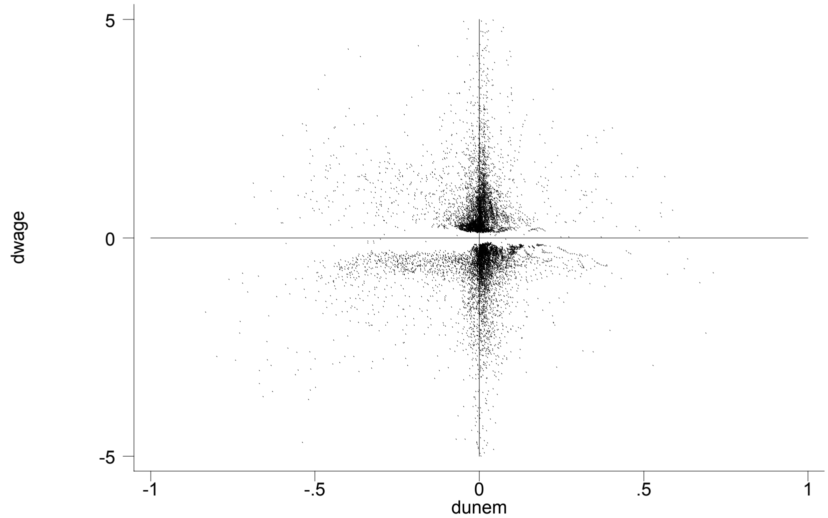
Note: dwage is the estimated change in the logarithm of the wage rate, *dunem* is the estimated change in the unemployment rate. Labor markets in the upper left are classified as ‘weakly adjusting in an increasing market’ (1) according to Table 1; those in the upper right are classified as ‘strongly rigid’ (2); those in the lower right as ‘weakly adjusting in a decreasing market’ (3); those in the lower left as ‘converging’ (4).

Figure B3 b: Graphical Illustration of Labor Markets with Insignificant Wage but Significant Unemployment Change (All Conceivable Labor Markets)



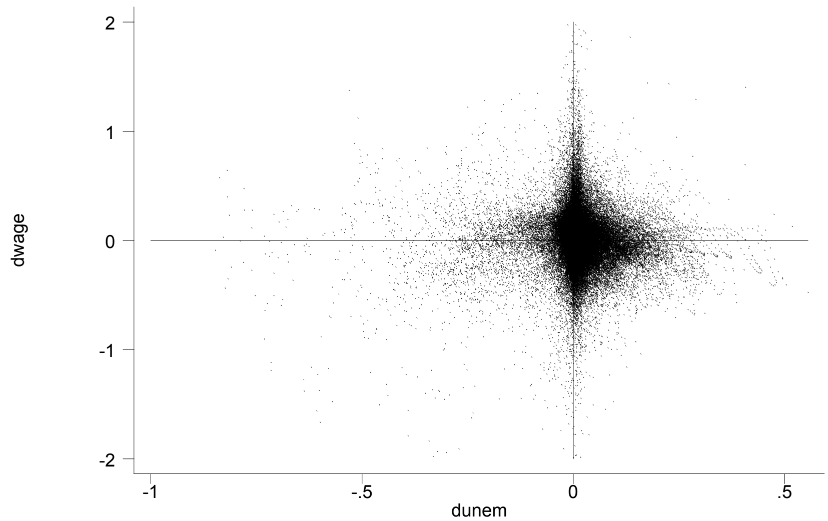
Note: Labor markets to the right of the vertical line are classified as ‘weakly rigid in a decreasing market’ (6), labor markets to the right of the vertical line as ‘weakly rigid in an increasing market’ (8).

Figure B3 c: Graphical Illustration of Labor Markets with Significant Wage but Insignificant Unemployment Change (All Conceivable Labor Markets)



Note: Labor markets above the horizontal line are classified as 'strongly adjusting in an increasing market' (5), labor markets below the line as 'strongly adjusting in a decreasing market' (7).

Figure B3 d: Graphical Illustration of Labor Markets with both Insignificant Wage and Unemployment Change (All Conceivable Labor Markets)

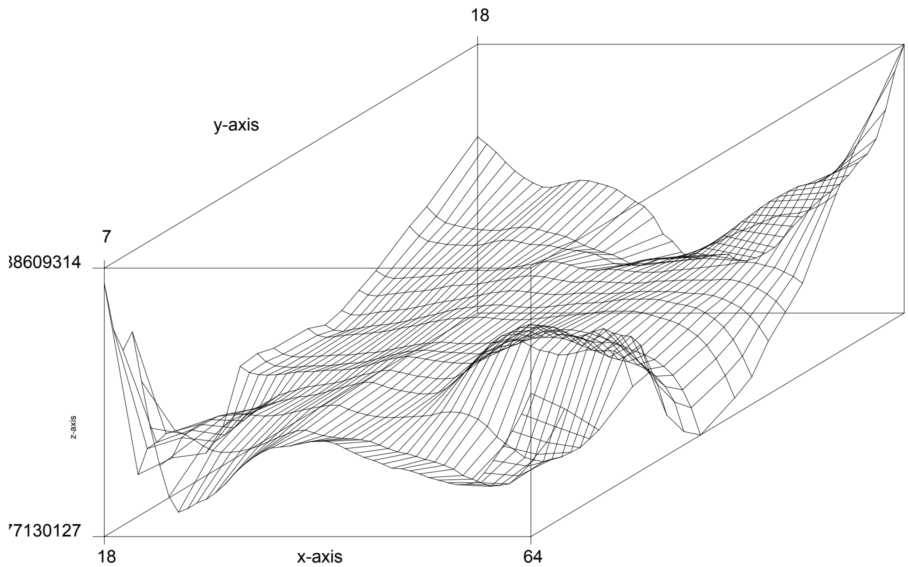


Note: dwage is the estimated change in the logarithm of the wage rate, *dunem* is the estimated change in the unemployment rate. All labor markets displayed are classified as 'stable in a stable market' (9).

The range of *dwage* has been censored in these graphs. However, only 0.8 percent of all labor markets exhibit a significant point estimate for the log wage change larger than 2 in absolute value.

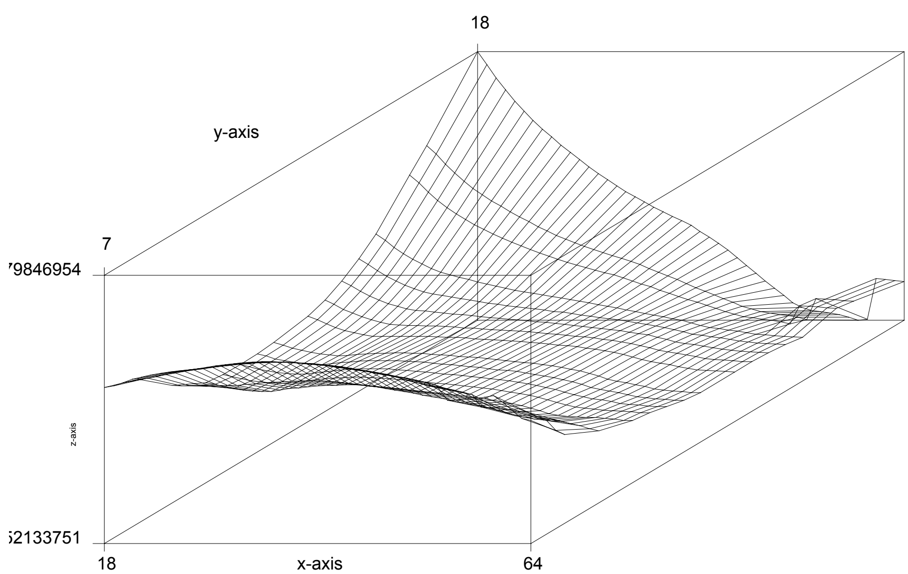
Source: GSOEP; own calculations.

Figure B4 a: Example Graph for Wage Change Estimates; Age on X-Axis; Education on Y-Axis (female, clerk, private sector industry, Nordrhein-Westfalen)



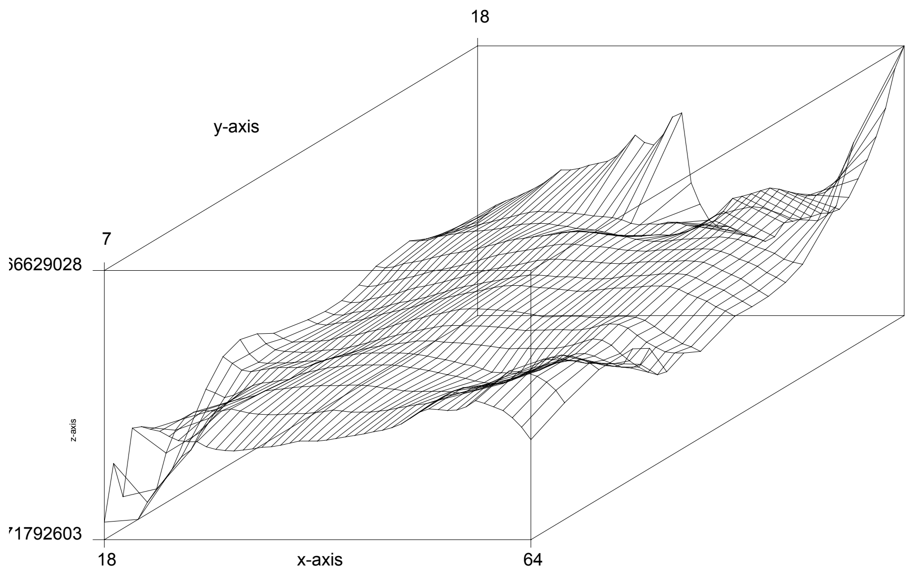
Note: The range of estimated log wage changes (plotted on the z-axis) is [-0.61, 1.12]. These point estimates are not necessarily statistically different from zero.

Figure B4 b: Example Graph for Unemployment Rate Change Estimates; Age on X-Axis; Education on Y-Axis (female, clerk, private sector industry, Nordrhein-Westfalen)



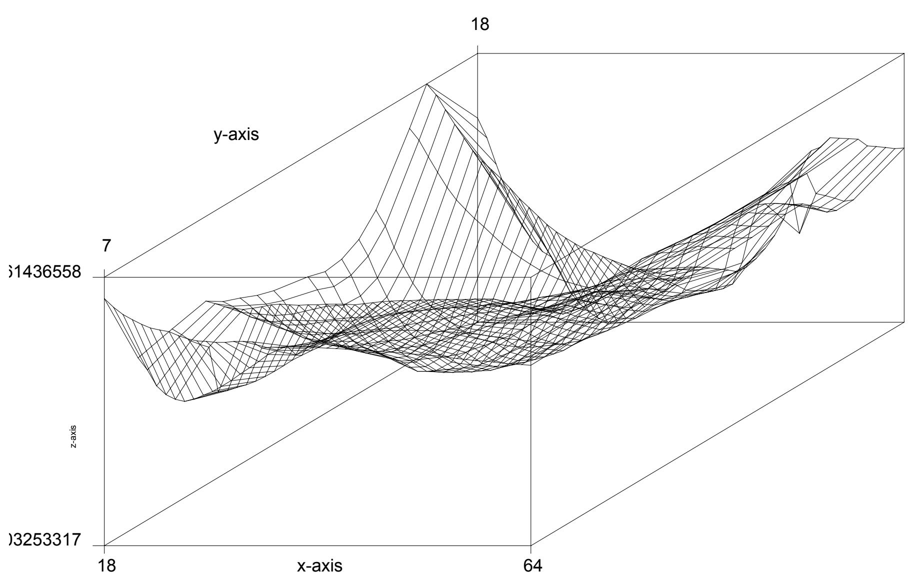
Note: The range of estimated unemployment risk changes (plotted on the z-axis) is [-0.04, 0.15]. These point estimates are not necessarily statistically different from zero.

Figure B4 c: Example Graph for Wage Change Estimates; Age on X-Axis; Education on Y-Axis (male, professional, public service sector, Northwestern Germany)



Note: The range of estimated log wage changes (plotted on the z-axis) is [-1.33, 1.59]. These point estimates are not necessarily statistically different from zero.

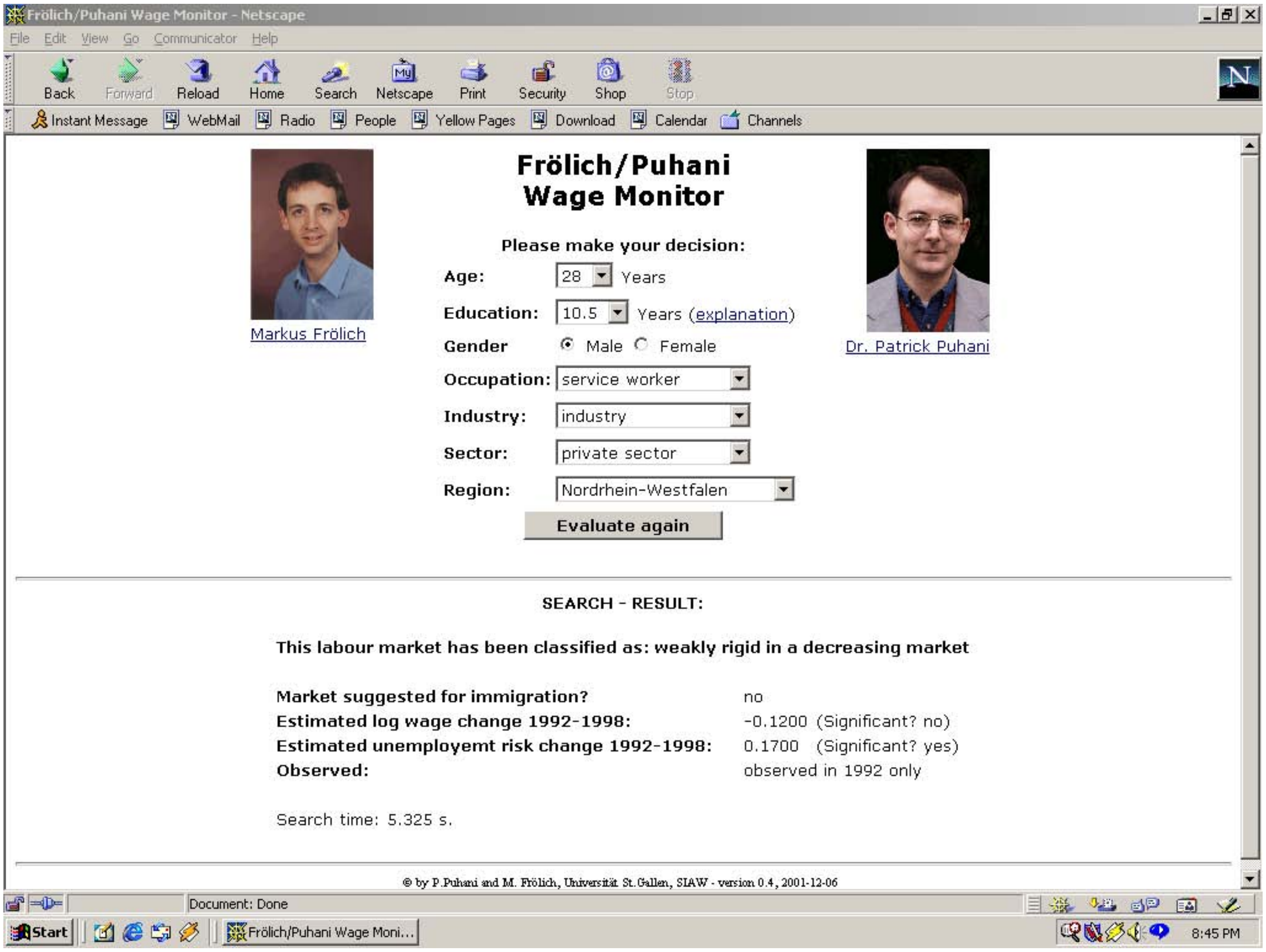
Figure B4 d: Example Graph for Unemployment Rate Change Estimates; Age on X-Axis; Education on Y-Axis (male, professional, public service sector, Northwestern Germany)



Note: The range of estimated unemployment risk changes (plotted on the z-axis) is [-0.02, 0.01]. These point estimates are not necessarily statistically different from zero.

Source: GSOEP; own calculations.

Figure B5: Internet Page with Detailed Estimation Results



Note: This page is accessible through http://www.siaw.unisg.ch/wagemonitor. The reader can enter the characteristics of a labor market of interest and obtain the corresponding nonparametric estimation and classification results.

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