BGPE Discussion Paper

No. 149

High-wage workers and high-productivity firms – a regional view on matching in Germany

Philipp Ehrl

May 2014

ISSN 1863-5733

Editor: Prof. Regina T. Riphahn, Ph.D.
Friedrich-Alexander-University Erlangen-Nuremberg

B G P E Discussion Paper Series

High-wage workers and high-productivity firms - a regional view on matching in Germany

Philipp Ehrl*

University of Würzburg‡

May 2014

Abstract

This paper analyzes assortative matching between employers and employees and its interrelations with the employment density of local labor markets in Germany. I devote attention to the identification of accurate quality measures: plants' total factor productivity and workers' fixed effect. Two different methods then yield evidence in favor of positive assortative matching. The correlation between both quality measures is positive. Wage gains amount up to 4% when both quality levels are equal. In a fairly general matching model, this shape of the wage curve arises due to complementarities of qualities in the production function. When generally higher productivities and wages in dense regions (caused by agglomeration economies and sorting) are not controlled for, the strength of matching and wage gains are overestimated. I also find that regional differences in matching quality cannot be attributed to the local density and unemployment rate.

Keywords: matching, agglomeration, unobserved skill, two-way fixed effects, TFP

JEL Classification: C78, J31, R11

*I would like to thank Stefan Bauernschuster, Christian Holzner, Malte Mosel, Michael Pflüger and seminar participants at the University of Passau, the ifo-Institute in Munich, the IPEA in Brasília, the BGPE conference in Bayreuth and the EALE in Torino for fruitful discussions and comments. Furthermore, I thank the Research Data Center (RDC) of the German Federal Employment Agency at the Institute for Employment Research for the data access, especially Mathias Dorner, Theresa Scholz and Simon Trenkle for their support. The data basis of this publication is the Linked Employer-Employee Data (LIAB, LM2). Data access was via guest research spells at the FDZ and via controlled data remote access.

‡Faculty of Economics, Sanderring 2, 97070 Würzburg, Germany. *philipp.ehrl@uni-wuerzburg.de*

1 Introduction

Workers have heterogeneous skills and firms have different requirements. This obvious fact has been incorporated in many papers on labor market matching, cf. the survey by Postel-Vinay and Robin (2006). Its way of modeling goes back to the seminal paper by Becker (1973). His insights on the theory of marriage are directly transferable to the matching between employer and employees. The main result is well-known: If complementarities between the quality of workers and firms exist and the market is frictionless, the optimal allocation corresponds to perfect positive assortative matching (PAM), i.e., the firm with highest quality employs the most productive worker, the second best firm employs the second best worker and so on. Due to the complementarity, the composition of matches has implications for the efficiency of the economy. If qualities are substitutes or completely unrelated, other matching patters arise. The actual allocation of workers to firms is ultimately an empirical question from which the type of production function can be deduced. In this regard, diverging assumptions can be found in the literature that, in turn, refer to diverging empirical findings on the existence of PAM (Eeckhout and Kircher 2011).

The present paper provides a comprehensive analysis of matching in the Germany and additionally considers its interdependencies with the employment density of regional labor market. Analyzing matching from a regional perspective has two merits. Facilitated matching is one possible formalization of the labor market pooling argument, e.g., in Wheeler (2001). The setting allows for testing of whether this is one of the reasons why a massive concentration of economic activity is observed in cities (Glaeser and Gottlieb 2009). Second, the existence of other agglomeration economies and the sorting of the most productive workers and firms to certain regions need to be controlled for, otherwise this co-location confounds the matching pattern.[1]

Apart from the consideration of the regional dimension, this paper contributes to the literature in two aspects. Before evaluating the implications of PAM, I devote attention to the question of whether PAM actually exists and how the measurement of qualities affect this assessment. This is the first attempt to capture matching with two direct quality measures: firms' total factor productivity (TFP) and worker fixed effects. As a second innovation, the paper considers two distinct methods to detect the matching pattern. In particular, I test the predicted wage curve from the matching model by Eeckhout and Kircher (2011) that permits a sound conclusion about the matching pattern and the type of underlying production function.

The innovations in my approach turn out to be relevant. I show that the frequently used firm fixed effects can be a misleading quality measure and that the application of this measure may explain prior dissenting findings.[2] Using the direct quality measure TFP, I find evidence for positive assortative matching. On the one hand, a positive correlation between the qualities of workers and firms is observed. On the other hand, the data suggests

[1] By sorting, I mean that high-productivity agents are attracted to a specific region (for whatever reason) without knowing their matching partner beforehand.

[2] Even though this study is based on plant level data, for convenience and for simplified comparison to other papers, I use the term 'firm'interchangeably.

that production efficiency and wages increase when the deviation of both quality levels is smaller. Both findings are less strong, but still significant after controlling for agglomeration economies and sorting. Finally, there is no convincing evidence that matching works better in labor markets where employment density or unemployment rates are higher.

The theoretical background of this paper is based on Becker (1973). Workers and firms are assumed to be heterogeneous in their qualities, both of which are comparable and have a clearly defined ranking.[3] If qualities are complementary, the equilibrium in a competitive but frictionless labor market is such that matching partners have same rank, i.e., are optimal. Shimer and Smith (2000) were the first to demonstrate that PAM still arises in the presence of search costs. However, neither firms nor workers are now willing to remain unmatched and search until the optimal matching partner is found, so that deviations within a certain tolerance range around the optimal match arise. Wheeler (2001) extends this basic setup by incorporating region-specific search costs in order to capture Alfred Marshall's idea of labor market pooling. According to Marshall (1890: 271), finding suitable labor and employment is easier in large markets, thus search costs are assumed to decline in the size of the region. This allows firms to choose more carefully, so that matching improves. However, the final result in Wheeler's model is ambiguous because the number of potential partners also grows with region size.

Eeckhout and Kircher (2011) build on the same basic matching framework to elaborate how assortative matching may be identified from wage data. Because data concerning qualities or productivities are typically unavailable, many papers follow Abowd *et al.* (1999) and use worker and firm fixed effect (FFE) estimates from a wage regression as proxies. Eeckhout and Kircher (2011) highlight that once wages are bargained over and firms account for their outside option of searching for a more accurate match, the wage is maximized when both qualities are equal, but as soon as the employer's quality dissents to either side, wages decrease. That is, the wage curve for a given worker has a bell-shaped curvature in the quality of her employer.[4] Therefore, the firm-specific part of the wage is not related to the quality of the firm, making FFE an uneligible proxy. Note that this critique does not invalidate the worker fixed effect (FE) as a quality measure. The worker FE is equal to the worker's mean wage (after accounting for other observable control variables in the regression) and thus reflects the labor market valuation of unobservable adherent skills. Nevertheless, the bottom line is that "based on wage data alone, it is not possible to determine whether sorting is positive or negative" (Eeckhout and Kircher 2011: 873). The present paper circumvents these problems by using TFP as a direct measure for firm quality.

In sum, the theoretical considerations imply two different methods of detecting the matching pattern and to obtain a conclusion regarding the type of underlying production function, given that reasonable quality measures are available. (1) Analyzing the correlation

[3] Another class of models incorporates differences in skill and job requirements as addresses on a unit circle, e.g., in Helsley and Strange (1990). Because it is not obvious how to assign productivity differences and a ranking to points on a circle, these models are not covered by the assortative matching perused in this paper.

[4] The model in Shimer and Smith (2000) also incorporates wage bargaining and yields a convex wage curve. In contrast, Wheeler (2001) assumes that the output of the match is divided into fixed shares, where workers' share is equal to their production elasticity.

between worker and firm qualities in the market. (2) Estimating the shape of the wage curve. The present data provide evidence for PAM with both approaches. Estimating a wage regression on the deviation of the optimal match within occupation and education groups confirms the bell-shaped relation. The significant second- and third-order terms imply wage gains of as much as 4% when the optimal partner is found. Gautier and Teulings (2006) derive a slightly different matching model and structurally estimate the implied wage curve. They also find a convex curvature and provide an estimate for the amount of search costs. Their worker quality measure does not contain unobservable skills, which, however, typically account for more than 60% of the total wage dispersion (Combes *et al.* 2008; Ehrl 2014). Moreover, a combination of industry and occupation dummies captures the quality of the firm but the latter may as well be understood as a worker-specific characteristic. Indeed, Ehrl (2014) finds that occupation is the most important observable wage determinant. Hence, my paper expands their approach with more accurate quality measures.

Many other empirical papers on assortative matching rely on the correlation between worker and firm FE. Abowd *et al.* (1999), Andersson *et al.* (2007) and Card *et al.* (2013) report a positive correlation, whereas Andrews *et al.* (2008), Gruetter and Lalive (2009) and Alda *et al.* (2009) obtain a large and highly significant negative correlation - all using the same methodology. Based on the present data, a direct comparison between TFP and the FFE estimates shows that both are quite unrelated. An inspection of the details in the estimations suggest that the use of additional control variables and the size of the data set substantially determine the value of FFE estimates.

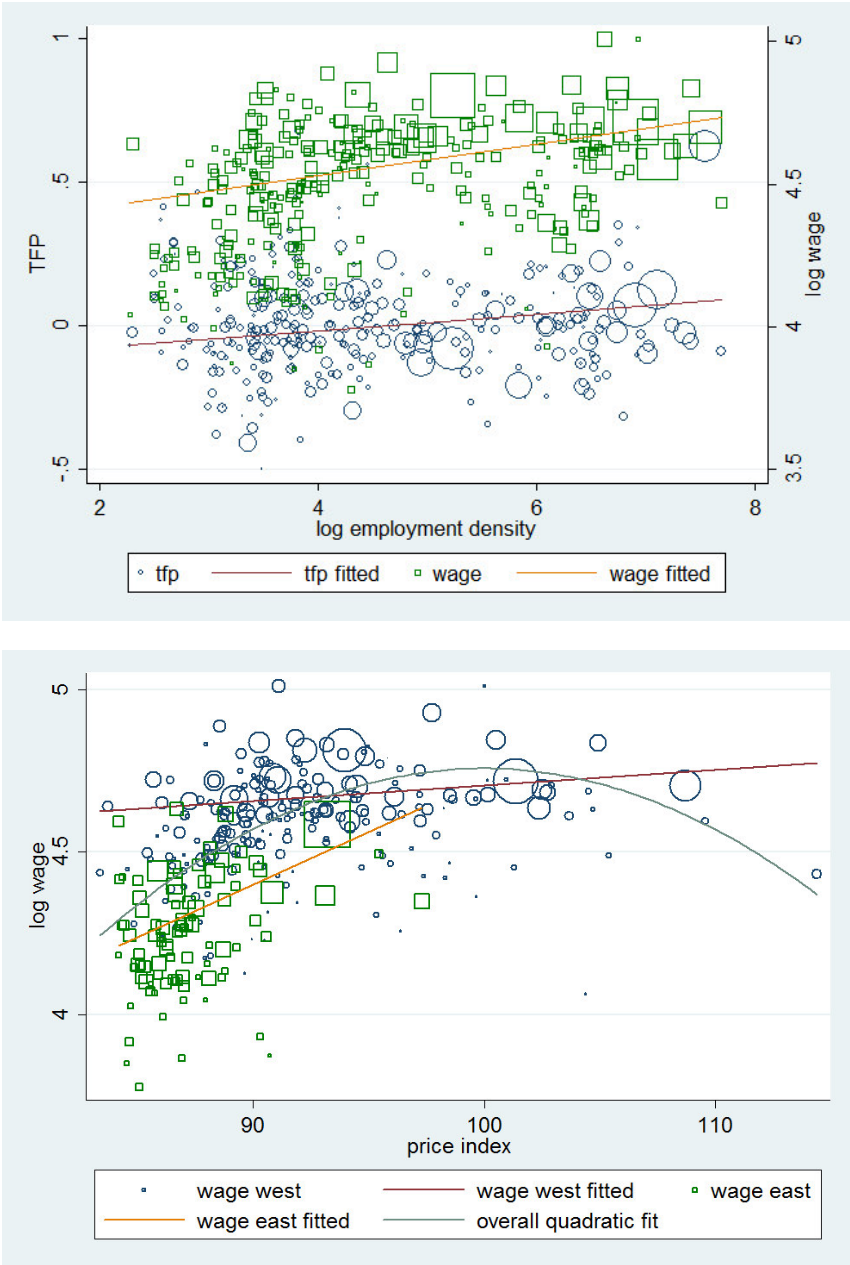
To the best of my knowledge, only two papers examine matching in the regional dimension. Both Mion and Naticchioni (2009) and Andersson *et al.* (2007) find that the most productive workers sort into densely populated regions. Furthermore, by being present in dense regions, workers and firms absorb a multitude of possible externalities through learning, sharing and matching, and therefore experience higher productivities and wages.[5,6] High price levels constitute another reason why wages are higher in agglomerations (Roback 1982). Figure 1 confirms the mentioned relations between TFP, wages, price levels and employment density using the present data set. This co-location itself generates a positive correlation between worker and firm quality. Mion and Naticchioni (2009) control for employment density but the correlation between firm size and a worker FE falls only slightly from 0.35 to 0.34. When I control for the agglomeration economies and sorting, the correlation between quality measures drops by about 2 percentage points, but the matching advantage implied by the wage curve is reduced by half. However, both results remain significant.

Finally, I find some evidence that the matching works best in medium-density counties, in accordance with the opposing effects identified in Wheeler (2001). However these results are

[5] See Duranton and Puga (2004) for theoretical evidence, Puga (2010) for a survey of empirical findings or Ehrl (2013) for evidence from Germany.

[6] A general note on the term 'matching'may be in order. Matching is understood as the assignment of workers to firms. When the search, selection and assignment work *better* in dense regions, matching transmits an agglomeration externality.

Figure 1: Mean wages, TFP, employment density and the price index at the county level



Notes: Each circle and square in the graphs represents a county-mean computed from the observations in the present LIAB sample. Both scatter plots and linear fits are weighted by the number of observations per county. The latter is represented by the size of the symbols in the graphs. In the first graph, the coefficient on TFP is 0.029 with an R^2 of 0.06 and the coefficient on wages is 0.055 with $R^2 = 0.16$. Both estimations are significant at the 0.01 level. In the second graph, East and West German counties show quite different coefficients (0.032 vs. 0.005) and R^2 (0.33 vs. 0.05). Note that the linear fit is shown separately for East and West Germany because without this differentiation, the data indicates that a inverted U-shape generates a better fit (R^2 =0.40). See section 2 for a detailed description of the variables.

not robust to different specifications. This ambiguity is in line with the opposed findings in Andersson *et al.* (2007) and Mion and Naticchioni (2009). The differences in their analyses are again my direct productivity measures and the estimation of a theoretically derived wage function that identifies a pecuniary advantage of matching. Delacroix (2003) argues that local differences in unemployment benefits may also generate labor market pooling.

Thereby, higher unemployment rates express the greater selectivity of agents that lead to better matches. Again, the present data does not support this prediction. Related studies by Ellison *et al.* (2010), Baldwin *et al.* (2010) and Ehrl (2013) use other specifications of labor market pooling (which are unrelated to the quality of agents) to show its positive effect on the local concentration and performance of firms.

The organization of the paper is as follows. The next section describes the data used. Section 3 discusses the identification of worker and firm qualities. Section 4 presents the results and some robustness checks and section 5 concludes the paper.

2 Data

The data underlying this study is the linked employer-employee data set (LIAB) from 1999 to 2007 provided by the German Institute of Employment Research (IAB), cf. Alda *et al.* (2005) for a detailed description of the LIAB. Its backbone is a survey of plants which is representative regarding the employment size of cells of a defined stratification matrix. This matrix is spanned by 10 establishment size classes, 20 sectors and the 16 Federal States. Within the cells, the selection of the sample is random, see Fischer *et al.* (2009) for details about the establishment panel. Only establishments with continuous responses in 1999-2001 or in 2000-2002 are selected into the LIAB sample. The given establishment information is detailed enough to estimate TFP from sector-specific plant-level production functions according to Levinsohn and Petrin (2003). For the detailed estimation procedure, see Appendix A.

For each of those plants, the LIAB contains information about all employees on 30 June in each year. Because the worker data is extracted from social security agencies, to which employers are obligated to report, the information about daily gross wages is highly reliable. However, around 12% of the observations exceed the social security contribution limit and the wage is top-coded. A common imputation procedure proposed by Gartner (2005) is therefore applied.[7] These gross average daily wages are then deflated by the national harmonized consumer price index. Another imputation rule is necessary for the education variable, which is unfortunately less reliable than wages. Education is unknown for about 11% of all observations and a large fraction of individuals exhibit chronological inconsistencies. Building on Fitzenberger *et al.* (2006), I remediate these entries relying on lagged and lead values, additional information on the occupational position and on "consistently" reporting employers. For the construction of my final sample, I exclude individuals with missing information (except for education), mini-jobbers, second and part-time jobs and

[7] Top coded wages are imputed using the predicted wage from a censored regression model plus an error term that is drawn from a truncated normal distribution. The censored wage regression includes the worker's occupation category (at the 3 digit level), a full interaction of a gender and West Germany dummy with six education categories, a dummy for German citizens, a quadratic in age and tenure, and dummies regarding the prior employment status. Without the error term, the correlation between the imputed wages and the covariates would be larger than the correlation between the latter and the uncensored wages. The error term's variance is equal to the variance of the wage estimates from the censored regression. Card *et al.* (2013) also use a similar procedure to impute top coded German wages.

establishments with poor matching quality.[8] Individuals with less than two observation, below the age of 19 or with more than 64 years are also dropped. The final sample contains 3,481 different plants, 529,422 individuals, or a total of 2,456,365 observations.

The spatial units in this investigation are counties (NUTS 3 level) and labor market regions. In 2007, Germany is divided into 438 different counties that differ considerably in their population density and size, cf. figure 1. Counties' employment densities and the unemployment rates will be used as controls and are taken from the Federal Statistical Office. The sample is further enriched by official county-level price indices. From 2006 to 2008 the Institute for Research on Building, Urban Affairs and Spatial Development (BBSR) gathered 7.3 million single prices of 205 different commodities in 57 commodity groups, covering the entire territory.[9] The computation is based on the same weighting scheme as the nationwide basket of commodities (Kawka *et al.* 2009). An alternative spatial delineation is used for two reasons. The number of plants per county-year is in some cases quite low, so that aggregated matching performance indicators may not be very reliable. In general, it is not granted that counties are the most appropriate approximation of local labor markets. Eckey *et al.* (2006) develop an aggregation of one or several counties into labor market regions, based on a factor analysis of commuting patterns. Within each of the resulting 150 labor market regions, the commuting time is below 60 minutes.

3 Identification of worker, firm and matching quality

The present paper focuses on labor market matching where agents are heterogeneous in quality, in the spirit of Becker (1973). Qualities (or traits in his case) are directly comparable and have a well-defined ranking, which makes only models of this kind accessible with the empirical test in this paper.[10] Define workers' productivity as $x \in [0; 1]$ and firms' productivity as $y \in [0; 1]$. An assignment of a worker with quality equal to x to a firm of quality y is denoted by $a(x) = y$. A match yields an output with a labor market value of $f(x, y)$. This production function $f(x, y)$ is twice continuously differentiable and increasing in its arguments. When the cross-partial of the production function is positive ($f_{x,y} > 0$), qualities of workers and firms are complements in production and the function is called supermodular. For frictionless labor markets Becker (1973) derives that output is maximized when matching is perfectly positive assortative, i.e., when $a(x) = x$. If the production function is submodular ($f_{x,y} < 0$) and qualities were substitutes in contrast, negative assortative matching would be optimal, i.e., $a(x) = 1 - x$. This demonstrates

[8] The IAB recommends that establishments where the information on total employees from the establishment data set deviates by more than 30% from the actual number of matched employees be discarded. I tighten this range to 10% for establishments with less than 50 employees. Additionally, I disregard observations with contradictory spatial information in both data sets. In total, this eliminates about 12% of matched observations.

[9] Aggregation of counties and weighting by the number of inhabitants makes it possible to use the price index even in the State of Saxony-Anhalt, where a territorial reform has taken place.

[10] The difference in the common framework based on the work by Diamond, Mortensen and Pissarides is that in their framework agents are also heterogeneous but the heterogeneity is disguised in the aggregate production function. Moreover, all matches have the same productivity and thus there is a unique wage rate in the market Pissarides (2000).

that the underlying production function determines the matching pattern. Vice versa, the observed matching pattern provides an opportunity to draw conclusions about the actual type of production function.

The following the argumentation is based on Eeckhout and Kircher (2011), who build on this basic framework and elaborate on how the matching pattern may be identified from wage data. An important assumption is wage bargaining between workers and firms, so that profits are given by $\pi(x, y) = f(x, y) - w(x, y)$. Without a partner, the income of all agents is equal to zero, and hence agents prefer to be matched. As soon as search costs are introduced, a certain tolerance range around the optimal match arises, because in case of applicants with a similar quality, it is not profitable to reject the current applicant, pay the search cost and wait for a better applicant.[11] Even though not every match is optimal, PAM is still present in the labor market, as derived by Shimer and Smith (2000). Search frictions make the model more realistic because each person has more than one possible employer. A proposition in Eeckhout and Kircher (2011) that I will test in the following is that from a given worker's point of view, the wage follows an inverted U-shape within the range of possible employers. Another important result is that the wage is maximized in the optimal match. Deviations in firm quality to *either* side decrease the wage, however. If a worker moves to a less productive firm, the output is lower and so is the wage. Deviation to a higher quality firm is not optimal for the new employer. If firms account for their outside option in the bargaining, they subtract the opportunity cost of matching with a better worker from the remuneration of labor. It is interesting to note that this argument does not depend on the type of the production function. For every supermodular production function, there exists another submodular function that induces an equal wage curve. Consequently, wage data alone does not allow us to draw any conclusions regarding the production function or the matching pattern. Information about firm qualities is necessary in order to judge whether the optimal match is given by $a(x) = x$ or $a(x) = 1 - x$.

For an empirical investigation, measures for worker and firm quality are obviously an essential requirement. Many preceding studies follow Abowd *et al.* (1999), who pioneered the simultaneous estimation of worker and firm fixed effects in wage regressions. These estimates were subsequently interpreted as quality measures. Consider the wage regression

$$w = \beta_z Z + v(x) + \delta(y) + \epsilon \tag{1}$$

with the worker FE $v(x)$ and the FFE $\delta(y)$ to illustrate their identification and interpretation. ϵ is the error term of the wage regression and Z represents additional observable and time-variant worker- and firm-specific control variables. $v(x)$ absorbs workers' average wage after controlling for the observable differences in Z. It represents the labor market value of unobservable and adherent skills and is thus suitable as a quality measure. Obvious observable quality measures only capture a small share of the variation in wages in empirical studies, cf. Ehrl (2014), and thus disregard important aspects of workers actual

[11] Obviously, introducing search cost explicitly requires a dynamic framework. The matching process considered here is sequential and excludes on-the-job search.

skills. Given that $\upsilon(x)$ already captures the average wage, the remaining wage variation oscillates around zero. Without movers, i.e., individuals who are employed for more than one firm, no payment differences between firms could be identified. Exactly those payment differences determine the value of the FFE. The crucial problem is that a given worker's wage difference in two distinct firms does not depend on the quality of the employer but only on the deviation between x and y, according to theory. If the quality of workers and firms are equally distributed in the population, no systematic deviation to either side is expected and thus "the only variation [in FFE] might arise from small sample properties that introduce non-systematic noise" (Eeckhout and Kircher 2011: 886). Therefore, the FFE is not an eligible quality measure.

There are two more effects that influence the value of the FFE estimates. In the real world, wages may be determined by characteristics other than qualities. Gender is an obvious example for a worker-specific attribute. Likewise, on the employer side, not all reasons for payment differences are related to quality or productivity. Cornelißen and Hübler (2011) find evidence that workers are compensated for lower job stability in high-wage firms. Wage differences may also be due to the local price and amenity levels (Roback 1982). In very beautiful places, a person might forgo some of her wage to enjoy living and working in that place. Then again, profuse housing and living costs in the largest cities justify wage premiums as compensation. Sectoral affiliation, firm size or coverage by a collective agreement constitute other payment differentials, cf. Gibbons and Katz (1992). Even if they are somehow related to the firm's productivity, these factors can be separated from the FFE if one is looking for an accurate quality estimate. It is important to keep in mind that if factors summarized by Z are not controlled for, their induced payment differentials are absorbed by the FFE estimate and thus $\delta(y)$ is not completely random, as conjectured by the simplified matching model. A sorting of high-quality workers into large firms may thus induce an upward-bias in the correlation between $\upsilon(x)$ and $\delta(y)$.

The second effect on the value of the FFE estimates is related to the number of movers in the data set. Fixed effect estimates can in general only be interpreted relative to each other. It is well known that in two-way FE models, the FFE may only be compared within a group of firms which is connected by movers between them. Andrews *et al.* (2008) prove that even within a mobility group, accurate estimation of FFE depends on the number of movers in each firm. The fewer movers there are, the more biased downwards the correlation between worker and firm FE will be. The authors show in simulations that this so called '*limited mobility bias*' is large enough to turn a true positive correlation into an observed negative one. In a follow-up paper, Andrews *et al.* (2012) vary the number of movers in the sample to demonstrate their finding empirically.

The bottom line is that for both theoretical and practical reasons, the use of FFE is far from optimal for testing assortative matching. At best, the FFE identify high-wage firms which are not necessarily high-productivity firms. To verify this conclusion and to test whether both measures imply a similar assortative matching pattern, I start by estimating a two-way FE wage regression model. Building on equation (1), my data permits the inclusion of observable characteristics of employees, employers and regions. To make the distinction between these dimensions clear, I denote them by X_i, Y_j and R_k, respectively. As argued above, the purpose for the inclusion of these control variables is that the higher the fit of the wage regression, the more they are an accurate measure for the adherent quality beyond the obvious payment differences. The regression is then given by

$$w_{it} = \beta_x X_{it} + \beta_y Y_{jt} + \beta_r R_{kt} + \gamma_t + \upsilon_i + \delta_j + \epsilon_{it} \tag{2}$$

where the dependent variable is the log daily wage of individual i in period t. X_{it} includes dummies for six education categories and dummies for five intervals of each tenure and age. At the level of firm j, I control for five employment size classes, the average working time, the share of high skilled personnel and whether the firm is covered by a company agreement, is part of a industry wide collective agreement, or orients itself to one. γ_t are time fixed effects and R_{kt} contains the county's log employment density, unemployment rate, local price index and a West dummy. Employment density in county k eliminates wage differences due to sorting, faster learning, etc. The unemployment rate accounts for local supply-side differences. As demonstrated in figure 1, the local price index and its square are also important wage determinants.[12] Finally, the worker and firm FE are denoted as in equation (1).

In a second specification, I replace the FFE by firms' TFP. The latter is estimated in a sector-specific plant-level production function following Levinsohn and Petrin (2003), cf. Appendix A. Estimation without FFE allows the inclusion of some more plant-specific categorical variables with little or no temporal variation: legal form, hierarchical level, industrial classification and a dummy for having a works council. These variables are summarized by the augmented vector $\tilde{Y}$ in the following regression.

$$w_{it} = \beta_x X_{it} + \beta_{\tilde{y}} \tilde{Y}_{jt} + \beta_p TFP_{jt} + \beta_r R_{kt} + \upsilon_i + \gamma_t + \epsilon_{it} \tag{3}$$

For the sake of better identification, equation (2) and (3) were estimated separately for males and females in East and West Germany, respectively. Because the identification relies on within-person variation and there are much less females than males in the data set, the fit of these regressions deteriorated significantly. This means that the fixed effects have a higher correlation with wages and that they absorb much more variation than in the pooled case. Obviously, the results from equation (2) were also worsened due to the lower number of movers within the four separate estimations. Slight differences in coefficients are less decisive here than reliable quality measures. For all that, the results in the paper remain qualitatively unchanged when the estimation is performed separately for women and men in East and West. Therefore, I prefer to present the pooled case and include controls for West and gender in the following regressions.

[12] Utilization of the price indices requires the assumption that these values are representative for all years in the panel since they are only compiled and available for 2006 and 2007. Note however, that none of the results is critical to the inclusion of the price index.

4 Results

4.1 Quality estimates, correlations and sorting

Table 1 indicates that the size and significance of most coefficients are similar across the two wage regressions. Almost all coefficients are significant below the 1% level and have the expected sign. Age and tenure reveal a inverted U-shape curvature. Remuneration increases monotonic with firm size and productivity, while the productivity effect is small compared to the effect of firm size. The regional characteristics are significant wage determinants only in the one-way fixed effects model.[13] Workers in West Germany earn an impressive 16% more than their East German counterparts. The coefficients of the price index confirm the bell-shaped relation in figure 1. A possible explanation for this finding are amenities. Counties with the highest living cost are expected to be the most beautiful and attractive areas, in line with Roback (1982). People thus might forgo a part of their wage to get a job in such a desired region.

Next, I perform a variance decomposition of the preferred specification (model 2 without the FFE) similar to Abowd *et al.* (1999). Except for the original log wage and the residual, each row in table 2 contains the effect of the components from the wage regression. The component effects are computed as the value of the variable multiplied by its estimated coefficient. Columns 1 and 2 show the variance of each component effect and its correlation with the log wage. The share of the covariance in the total variance of individual wages in column 3 states the importance of each effect. Note that the variance decomposition is exactly additive, so all shares in column 3 add to one.

The positive and relatively important effect of firm size confirm the prior assessments. However, the total share of the observable characteristics is small. For example, all observed individual characteristics only explain 5.3% of the total wage variation, whereby education already accounts for 4.9%. The West dummy (7.7%) and all employer attributes (3.3%) also have little explanation power, compared to the overwhelming contribution of the worker effects. This is the usual finding, e.g., in Abowd *et al.* (1999) or Combes *et al.* (2008).

The interest in this study lies in the correlations between the component effects in each row and the worker FE, density and West dummy, respectively, as shown in columns 4-6. From the correlation with v_i, we see that workers with favorable observable attributes also have higher unobserved skills. Most important for this paper is the positive correlation between v_i and TFP. Although, the coefficient of 0.09 is small, the correlation is more appropriately taken at the level of employer-employee pairs or at the firm-level, cf. table 3. Still, this result is a first sign that PAM is present in the German labor market. The last two columns show that agglomeration economies or sorting of the largest and most

[13] The reason for the low significance of regional characteristics in the two-way FE model is that their identification is based on movers, as is the identification of the FFE. The coefficient of the West dummy cannot be identified at all because there is no individual that moves between two firms in East and West Germany. To maximize the number of movers in the two-way FE estimation, the sample is not based solely on firms for which enough information is available to estimate TFP. On the other hand, firms are lost that do not belong to the largest group of employers connected by movers, which explains the different number of observations between the two models in table 1.

Table 1: Wage regressions

model	two-way FE		only worker FE	
2.education	0.0387	(0.0021)***	0.0391	(0.0030)***
3.education	-0.1537	(0.0161)***	-0.1484	(0.0239)***
4.education	0.0616	(0.0050)***	0.0635	(0.0070)***
5.education	0.1765	(0.0075)***	0.1680	(0.0093)***
6.education	0.2094	(0.0067)***	0.1975	(0.0091)***
2.tenure	0.0368	(0.0003)***	0.0360	(0.0004)***
3.tenure	0.0478	(0.0005)***	0.0458	(0.0006)***
4.tenure	0.0441	(0.0006)***	0.0369	(0.0008)***
5.tenure	0.0313	(0.0008)***	0.0221	(0.0010)***
2.age	0.0431	(0.0007)***	0.0441	(0.0009)***
3.age	0.0533	(0.0008)***	0.0547	(0.0010)***
4.age	0.0439	(0.0009)***	0.0456	(0.0011)***
5.age	0.0246	(0.0010)***	0.0265	(0.0013)***
works council			0.0106	(0.0007)***
2.vertical type			-0.0065	(0.0004)***
3.vertical type			-0.0019	(0.0004)***
4.vertical type			0.0171	(0.0009)***
2.legal form			0.0154	(0.0028)***
3.legal form			0.0082	(0.0027)***
4.legal form			0.0150	(0.0029)***
5.legal form			0.0274	(0.0038)***
6.legal form			0.0117	(0.0038)***
2.size	0.0395	(0.0103)***	0.0476	(0.0050)***
3.size	0.0604	(0.0105)***	0.0752	(0.0052)***
4.size	0.0844	(0.0105)***	0.1059	(0.0053)***
5.size	0.0987	(0.0105)***	0.1333	(0.0054)***
TFP			0.0162	(0.0005)***
working hours.	-0.0021	(0.0001)***	-0.0011	(0.0001)***
sector agreement	0.0113	(0.0007)***	0.0126	(0.0007)***
sect. agrmnt. orient.	0.0114	(0.0006)***	0.0102	(0.0006)***
company agreement	0.0078	(0.0007)***	0.0031	(0.0007)***
HQ share	0.0068	(0.0005)***	0.0171	(0.0006)***
log density	-0.0003	(0.0007)	0.0089	(0.0013)***
price index	0.0042	(0.0249)	0.1040	(0.0262)***
(price index)^2	0.0001	(0.0001)	-0.0006	(0.0001)***
unemployment rate	-0.0024	(0.0001)***	-0.0023	(0.0001)***
west			0.1655	(0.0255)***
constant	3.7014	-	-0.6395	(1.2279)
worker FE	✓		✓	
plant FE	✓		✗	
sector FE	✗		✓	
time FE	✓		✓	
F	29.85	(0.00)***	1046.91	(0.00)***
N	2,874,096		2,456,365	

Notes: The first two columns report the results from estimation of equation (2) and the last two columns pertain to equation (3). Robust standard errors are in parentheses and significance levels of 0.01 are denoted by ***. Variables that begin with a number denote one of the dummies of the respective categorical variable. For example, 2.*education* shows the additional returns for workers with the second lowest education category compared to workers in the omitted category, namely the first and lowest. Tenure, age, and plant size are captured by dummies for the following three intervals. Tenure (in days): [1000, 3000, 5000, 9000, 13000, 13000+], age [25, 35, 45, 55, 64], plant size [9, 49, 199, 999, 1000+];

Table 2: Variance decomposition

	var(·)	corr(·, w)	$\frac{cov(\cdot,w)}{var(\cdot,w)}$	corr(·, υ_i)	corr(·, dens.)	corr(·, west)
wage	0.1317	1	1	0.9208	0.2207	0.3901
all worker observables	0.0027	0.3710	0.0533	0.3145	-0.0059	-0.1290
education	0.0024	0.3640	0.0487	0.3165	-0.0046	-0.1178
tenure	0.0002	0.0377	0.0013	0.0204	-0.0139	-0.0837
age	0.0001	0.0968	0.0033	0.0623	0.0076	0.0052
all firm observables	0.0009	0.4170	0.0339	0.2958	0.3042	0.3521
TFP	0.0000	0.0669	0.0009	0.0888	0.1337	0.0027
firm size	0.0006	0.3676	0.0247	0.2399	0.2642	0.3748
sector FE	0.0006	0.1602	0.0113	0.0314	-0.2726	0.1808
time FE	0.0004	0.0840	0.0046	0.0138	0.0052	0.0319
west	0.0052	0.3901	0.0774	0.1673	0.1625	1
density	0.0002	0.2207	0.0078	0.2068	1	0.1625
unempl.	0.0002	0.2735	0.0093	0.0994	-0.0368	0.7710
PI	0.0008	0.0555	0.0042	-0.0426	-0.2296	0.0032
υ_i	0.0860	0.9208	0.7440	1	0.2068	0.1673
residual	0.0072	0.2331	0.0544	0.0000	0.0000	0.0000

Notes: Variance decomposition after estimation of equation (3). The number of observations is 2,456,365. The rows refer to components or aggregates of components included in the wage regression. The columns display the variance of these estimated components of the wage regression. Column 2 displays the components' correlation with wages. Column 3 lists the quotient of covariance and variance of the estimated components with wages. The correlation between component effects and the effects of worker FE, employment density and the west dummy are listed in the last four columns, respectively.

productive plants into West Germany and into dense counties are at work. The same is true for the skilled workers, albeit only regarding their unobserved skills.[14]

After this closer look at the preferred specification, I compare the quality measures between the two regression models. Table 3 shows that the two worker FE are considerably different, given that they are supposed to reflect the same ranking of skills. As in a variety of preceding papers, the two-way FE model is highly suggestive of negative assortative matching. Warned by the theoretical considerations, I do not take this result at face value. In fact, the data proves that FFE have little to do with total factor productivity. For the remainder of the paper, I focus on TFP as the measure of firm quality.

By considering these findings, the theoretical considerations in section 3 and looking more closely at the details of the different estimations, a certain pattern emerges that may explain previous results. It seems that both the size of the data set and the type of firm-specific control variables generate interfering effects. My two-way FE model with several additional firm-specific controls suggests that matching is negative assortative. Andrews *et al.* (2008) estimate a similar model with related German sample data and obtain a similar result. In their follow-up paper Andrews *et al.* (2012) have access to data on the population and

[14] At this disaggregated level the strength of sorting is much higher than in Combes *et al.* (2008), who obtain a correlation of 0.1 for their de-trended area-time fixed effects.

Table 3: Correlation table - comparison of specifications

	$\upsilon_{i,FFE}$	$\upsilon_{i,PFE}$	FFE	TFP
$\upsilon_{i,FFE}$	1			
$\upsilon_{i,PFE}$	0.7642	1		
FFE	-0.4176	0.1779	1	
TFP	0.0312	0.0791	-0.0313	1

Notes: The cells display the correlations between the estimated worker FE $\upsilon_{i,FFE}$, the firm fixed effects, both from the two-way fixed effects model in equation (2), the TFP, and the worker FE $\upsilon_{i,PFE}$ from the model in equation (3) with personal fixed effects only. The number of observations is 2,084,588.

demonstrate the existence of the limited mobility bias directly. Varying the share of movers in the data between 10% and the complete 100% increases the correlation between worker and firm FE from -20% to +25%. Likewise, Andersson *et al.* (2007) and Card *et al.* (2013) work with very large data sets and obtain a positive correlation. However, their regressions do not include observable firm-level variables, so that positive effects of firm size, etc. are still embodied in the FFE. This effect becomes obvious in the present study and in Mion and Naticchioni (2009), who use firm size as the employer quality measure. The latter's correlation with the worker FE is 0.35, whereas I obtain a correlation of 0.24. On the contrary, Alda *et al.* (2009) control for even more characteristics than in equation (3), some of which *reduce* the firm's remuneration, and they obtain a less negative matching pattern. This suggests that the observed matching pattern depends on how the qualities are defined and estimated.

Having obtained estimates for both individual and firm quality, the sign and strength of matching is captured in two different ways. (a) The traditional method employed so far is to compute correlation coefficients between υ_i and TFP. In the following, I strengthen the finding by varying the observation level and control for agglomeration economies and spatial sorting. (b) I analyze the the deviation between both qualities in a match and its relation to wages. This approach is detailed in the next subsection.

Tables 3 and 2 are already suggestive of positive assortative matching. In order to avoid biases due to the differing number of observations per match in the unbalanced panel, correlations are recalculated at the level of firms and employer-employee pairs in table 4. In the latter consideration, every match has the same weight and long-lasting employment relations do not enter with greater weight in the calculation of the correlation. At the employer-employee-level the value increases slightly to 0.10 and the correlation of a firm's TFP and the average worker effect of its employees in a given year is 0.17.

The next exercise verifies whether the observed PAM is merely due to sorting or co-location of productive firms and workers in certain areas. The positive correlations between TFP, υ_i and employment density observed in table 2 and figure 1 give reason to presume that sorting plays a role. Sorting of workers to places with high amenity levels may also be an issue. Moreover, agglomeration economies lead to higher productivity and wage levels, cf. Puga (2010). These externalities can be best captured at large in a black-box manner by the local employment density. Finally, Van den Berg and Van Vuuren (2010) are concerned that an observed matching pattern might not necessarily be caused by PAM but by variations in search frictions across markets.[15] At the same time, the authors note that employment density may be regarded as a reasonable approximation for the degree of local search frictions. Thus, controlling for density and the price index takes all of those concerns into account. Table 4 shows that the strength of matching falls to 0.06 at the employer-employee level and to 0.14 at the establishment level, after controlling for the regional employment density and the price level. On the one hand, this demonstrates that the spatial structure is indeed important and partly explains the observed positive correlation. On the other hand, these factors still do not eliminate the observed positive and significant allocation of high-quality workers to high-quality firms, even though the correlations are rather small.

Table 4: Correlations of TFP

	employer-employee level			firm-year level		
υ_i	0.1037	0.0761	0.0591	0.1698	0.1522	0.1475
log density		0.1323	0.0013		0.0544	0.0348
price index			0.1497			0.0139

Notes: The cells display correlation coefficients between worker and firm quality at different observation levels. Simple correlations are shown in column 1 and 4. The second and the fifth columns show partial correlation coefficients between TFP and either worker quality or density, where the respective other variable is controlled for. The same applies in in columns 3 and 6, where the local price index is additionally controlled for. The worker FE υ_i are taken from model 1. The number of observations is 551,047 for the employer-employee pairs and 14,676 at the firm-year level. All correlations are significant below the 1% level.

4.2 Deviations from the optimal match

So far, we have looked at simple correlations whose absolute value is not straightforward to interpret. Nor do the correlations tell whether the matching quality has an effect on production efficiency or workers' wages. Therefore, I implement the structural test of the wage curve derived by Eeckhout and Kircher (2011). Section 3 explained why a given worker's wage exhibits an inverted U-shape in firm quality, having its maximum at the optimal match. Under supermodularity, for which we have seen some evidence so far, the optimal match is given when both qualities are equal. Because both the mass of worker and firm qualities are centered around zero in the data, the deviation from the optimal match can be defined as $k_{ij} \equiv \upsilon_i - TFP_j$.[16] In a frictionless labor market, all realized matches should theoretically be perfect, i.e., $k_{ij} = 0$. It is unquestionably more realistic to assume the existence of search frictions, whereby deviations from the optimal match are also a possible equilibrium outcome. For the empirical identification of the bell-shaped relation between wages and k_{ij}, these deviations are an essential requirement (Eeckhout and Kircher 2011). Gautier and Teulings (2006) also derive a matching model with the

[15] I will investigate this regional pattern further in subsection 4.3.

[16] Instead of the deviation in absolute terms, one may consider the difference between the ranks of both qualities in their distributions. As noted further below, this yields the same result.

same prediction and provide a consistent structural estimation of its wage curve. They focus on the distinction between a frictionless world and a labor market with search cost. Another difference is that their proxies for the agents' qualities are less indicative and do not go beyond observable characteristics. Gautier and Teulings (2006) find a concave wage curve, which is interpreted as evidence in favor of search frictions.

At first sight, one is tempted to estimate the effect of $(\upsilon_i - TFP_j)$ on w_{ij}; however, a difficulty arises from this regression. Unlike in the model, firms actually require more than one worker for production. In a country-wide comparison Lazear and Shaw (2009: 41) find that "most firms do reflect a subsample of many of the jobs done in the economy" and that the wage dispersion within firms is similar to that of the whole economy. The problem is that wages and especially qualities are not yet comparable across workers. Consider that workers with a high salary, on average, have a high estimated υ_i.[17] Consequently, when a high-TFP firm hires a blue collar worker this would generally seem like a bad match, whereas hiring a PhD graduate appears to be a good match. This disregards the fact that there are still adherent differences between each type of worker. For example, some PhD graduates are more productive, while some are less productive in their current job. Therefore, once we decide to estimate the equation across all workers, one needs comparable wage levels and worker qualities.

Education and occupation are the most obvious and important wage determinants and quality indicators, cf. Ehrl (2014). To overcome the qualities' apparent lack of unified measurement, I test the matching hypothesis within education-occupation groups. The worker FE and the wage without the worker FE part are regressed on 6 education dummies, 20 occupation segments[18], and a West and a gender indicator variable. The residuals in these regressions are defined as the adjusted wage $\tilde{w}_i$ and adjusted quality $\tilde{\upsilon}_i$ that are used in the following. The results of these regressions are omitted for brevity, but all coefficients are highly significant and these variables explain about 53% and 30% of the variation in the wage and in υ_i, respectively. Three more indicator numbers document the necessity and success of the transformations for the proper calculation of deviations from the optimal match. On the one hand, the correlation coefficient between the adjusted worker quality $\tilde{\upsilon}_i$ and TFP remains unchanged at 0.10 and the correlation between $\tilde{\upsilon}_i$ and υ_i is 0.83. On the other hand, the strong relation between the adjusted wage and $\tilde{\upsilon}_i$ shrinks to 0.09 from originally 0.92. Hence, the relative order of $\tilde{\upsilon}_i$ is left almost unchanged, while only their levels are now comparable among each other.

Now, the requirements are made to compute the deviation from the optimal match as $\tilde{k}_{ij} \equiv \tilde{\upsilon}_i - T\bar{F}P_{i\in j}$ and estimate its effect on $\tilde{w}_{ij}$.[19] The significant negative third-order

[17] Recall that υ_i is defined as a worker's mean wage less the fitted values from equation (3) and compare the strong correlation between υ_i and w_{it} in table 2.

[18] The delineation of occupations into "segments" is developed by Matthes *et al.* (2008) to increase the similarity of tasks and skill requirements within segments compared to the official 2-digit occupational classes.

[19] Note that υ_i is time invariant and that an estimation in the worker-year panel would give those matches a higher weight that have more observations. Only changes in the TFP (for whatever reason) change the assessment of the match and introduce noise. I prefer to estimate at the employer-employee level and use the mean values $T\bar{F}P_{i\in j}$, i.e., the mean TFP while individual i was employed in firm j.

terms of $\tilde{k}_{ij}$ in columns 1 and 2 of table 5 confirm the expected bell-shaped relationship. A male and a West dummy in column 3 neither show any significant effect nor change the coefficients of $\tilde{k}_{ij}$ much. By adding the regional log density, unemployment rate, price index and its square to the regression in column 4, the fit of the regression is raised, the result does not change.[20] When the computation of the deviation from the optimal match is based on the rankings of the two qualities instead of the values of $\tilde{v}_i$ and TFP, repeating the regression in table 5 confirms the highly significant inverted U-shaped relationship.

Table 5: Wages and the deviation from the optimal match

	[1]	[2]	[3]	[4]
$\tilde{k}_{ij}$	0.0224	0.0285	0.0224	0.0134
	(0.0102)**	(0.0127)**	(0.0102)**	(0.0046)***
$\tilde{k}_{ij}^2$	-0.0278	-0.0280	-0.0281	-0.0212
	(0.0084)***	(0.0083)***	(0.0088)***	(0.0055)***
$\tilde{k}_{ij}^3$	-0.0124	-0.0260	-0.0125	-0.0085
	(0.0043)***	(0.0099)***	(0.0044)***	(0.0020)***
$\tilde{k}_{ij}^4$		-0.0043		
		(0.0022)*		
west			-0.0013	-0.0220
			(0.0066)	(0.0070)***
male			-0.0011	-0.0032
			(0.0021)	(0.0013)**
regional controls	✗	✗	✗	✓
constant	4.3595	4.3596	4.3614	-1.3401
	(0.0033)***	(0.0033)***	(0.0053)***	(0.4222)***
R^2	0.0258	0.0276	0.0259	0.3317
F	4.21	3.60	2.87	46.87
N	551047	551047	551047	551047

Notes: The dependent variable is the adjusted log wage rate, as described in the main text. Cluster-robust standard errors at the firm-level are in parentheses and significance levels of 0.1, 0.05 and 0.01 are denoted by *, ** and ***, respectively.

The shape of the relationship from column 1 is displayed non-parametrically in figure 2.[21] For the range between -0.8 and 1, where more than 90% of all observations are located, the scatter plot accords well with the theoretical predictions. The inverted U-relation peaks close to zero, where the worker quality is exactly equal to the firm quality. Thus, following the idea of Eeckhout and Kircher (2011), the data reveals that the education- and occupation-independent part of the wage increases with the matching quality. This reveals the positive efficiency effect in the production function that causes PAM. To give a rough interpretation in monetary terms, the difference between the lower right end (4.32) and the peak amounts to 3.5€ per day. Hence, the average income loss in bad matches

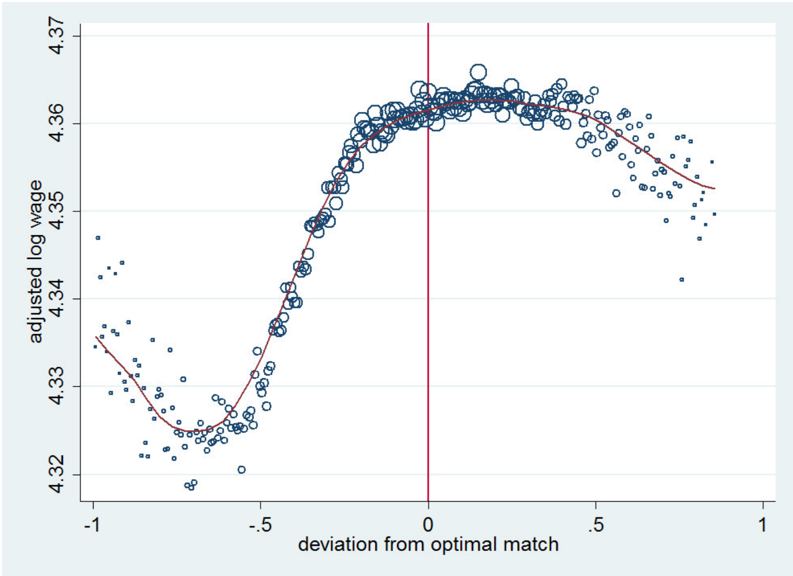
Notwithstanding, both possibilities essentially produce almost the same results.

[20] Using a cluster bootstrap with 500 replications virtually yields almost the same standard errors as in table 5.

[21] Due to privacy protection requirements and for the ease of graphical representation, I divided the matching quality distribution into 1000 equally spaced segments. In each of these segments the mean wage is represented by a dot in the graph. Segments with less than 150 observations are omitted, which eliminates outliers at the margins of the distribution.

compared to good matches is 4% of wage income. When subject to the regional controls, the predicted curve in column 4 is flatter. It implies that the maximum income gain is reduced to 2%. Once more, without the regional controls, the positive assortative matching does not vanish but would instead be overestimated.

Figure 2: Wages and the deviation from the optimal match



Notes: The graph shows the mean adjusted log wage of individuals in 1000 equally spaced segments of the distribution of $\tilde{k}_{ij}$ and a locally weighted polynomial fit. Both are weighted by the number of individuals that each segment represents.

4.3 The spatial pattern of matching

The previous subsection demonstrates that accurate matches have a positive effect on production efficiency and wages. The consecutive question for policy makers is how such favorable matches may possibly be stimulated? To this end, I examine regional differences in the matching pattern. Marshall (1890) already noted that a larger market size yields better expected matches between workers and firms and makes a location seem more attractive. Wheeler (2001) integrates Marshall's idea of labor market pooling in a matching model, which is close to the one described in section 3, by assuming that search costs decline with the size of the local labor market. However, only under certain conditions does Wheeler's model predict that larger regions imply a smaller tolerance range of acceptable matches and thus more efficient production, because two countervailing forces are at work. Lower search costs induce firms to remain unmatched for a longer time and search more carefully for an employee with a quality close to their own. On the other side, the pool of potential partners is larger, which makes the search more complex. Using a similar framework, Delacroix (2003) argues that differences in unemployment benefits may be responsible for labor market pooling. These benefits also reduce the cost of waiting to be matched, cause an intensified search and lead to better matches. An unpleasant side effect in these formalizations is that better matching comes along with higher unemployment rates in agglomerations. Unemployment benefits or other possible reasons that induce workers to search more carefully are unobservable in my data. Therefore, the local unemployment rate is used as a proxy for these mechanisms.

These predictions are jointly tested using both matching indicators derived above. To this end, I compute (a) regional correlation coefficients between $\tilde{v}_i$ and TFP; and (b) the average deviation between both quality measures in a county (German NUTS-3 regions). These matching indicators are then regressed on the local unemployment rate, the employment density and its square in order to account for the countervailing forces described previously. The results are shown in table 6, where all estimations are weighted by the number of employees in each county. Column one suggests that better matches are obtained where the unemployment rate is high. However, this observation vanishes once general differences between East and West German counties are controlled for. Both the unemployment rates and employment densities are quite different between both parts of Germany, cf. the last column in table 2. Instead, the data reveals that there is a slightly significant and non-linear effect of density. In column three, the matching quality is computed with the unadjusted worker fixed effect, but it essentially yields the same results. The significance of employment density and its square suggest that matching works best in medium-dense counties, because the peak of the implied matching quality curve lies roughly in the middle of the density distribution, at about 148 employees per square kilometer.[22] In line with Wheeler (2001), it seems that it is difficult for firms to obtain the most suitable staff, once the local labor market is too crowded and the choice becomes too complex. Up to a certain point, however, the firms benefit from a larger pool of potential candidates.

In column four, where the matching quality is captured by the deviation from the optimal match, I use the absolute value of $\tilde{k}_{ij}$ as dependent variable. Because the best match corresponds to $\tilde{k}_{ij} = 0$, no matter if the relation between $\tilde{k}_{ij}$ and density is positive or negative, the curve would be described by an implicit function.[23] Estimation with $\left|\tilde{k}_{ij}\right|$, the matching quality exhibits a U-shaped form in density, where the minimum is in the middle of the density distribution. Moreover, the matching quality is unrelated to the unemployment rate. It is thus reassuring that both matching indicators produce the same finding.

A potential concern is that some values of the matching indicator may be based on few firms.[24] To check the robustness of the finding, I exclude county-years with less than 30 observations and obtain essentially the same result. Second, the spatial delineation of region is based on arbitrary political boundaries and may generally distort the findings (Briant *et al.* 2010). Therefore, the analysis is repeated with correlation coefficients computed at the level of larger labor market regions. It turns out that the significance of the coefficients in table 6 are not robust to a reconsideration at the labor market regions. In line, previous studies find diverging results as well. Andersson *et al.* (2007) show that the correlation between worker and firm effects strictly increases in the region's density. Contrary, Mion

[22] Density is defined as the number of employees per square kilometer. Densities of German counties varies between 7 in Mecklenburg-Strelitz and 2200 in Munich.

[23] This can be easily seen by rotating figure 2 and substituting density for the wage on the axis.

[24] Indeed, not all of the counties are included because the calculation of the correlation coefficients requires two or more firms per county.

and Naticchioni (2009) report for Italian provinces that the extent of matching decreases in density. Summing up, the matching quality can only be predicted to a small extent by the local employment and unemployment densities in Germany.

Table 6: The spatial pattern of matching

dependent variable	$corr\left(\tilde{u}_i, TFP_{jt}\right)_{kt}$		$corr\left(u_i, TFP_{jt}\right)_{kt}$	$\left\|\left(\tilde{k}_{ij}\right)_{kt}\right\|$
log density	0.1364	0.1496	0.1846	-0.1415
	(0.0910)	(0.0863)*	(0.0841)**	(0.0643)**
(log density)^2	-0.0137	-0.0147	-0.0177	0.0144
	(0.0087)	(0.0084)*	(0.0081)**	(0.0066)**
unemployment	0.0052	0.0016	0.0015	-0.0011
	(0.0021)**	(0.0042)	(0.0041)	(0.0018)
west		-0.0551	-0.0586	-0.0359
		(0.0527)	(0.0510)	(0.0207)*
constant	-0.3155	-0.2708	-0.3607	0.6189
	(0.2289)	(0.2385)	(0.2354)	(0.1588)***
R^2	0.0186	0.0229	0.0269	0.0887
F	2.18	2.16	2.70	5.33
N	2244	2244	2244	3002

Notes: The aggregation level of all variables is county-years. The dependent variable in column 1 is the correlation coefficient between the (unadjusted) worker quality and the employer's TFP in each county k. The dependent variable in columns 2 and 3 uses the adjusted worker quality instead. In the last column, the dependent variable is computed as the average deviation between workers' and firms' qualities in each county. Estimations are weighted by the number of workers in k and standard errors in parentheses are clustered at the county-level. Significance levels of 0.1, 0.05 and 0.01 are denoted by *, ** and ***, respectively.

4.4 Robustness

Beyond the re-aggregation of spatial units from counties to labor market regions and the disposition of two different matching measures, I provide four more robustness checks. One potential concern may be that this study includes manufacturing and non-manufacturing industries.[25] In the latter sectors, the matching, wage setting and the production functions and the productivities might be different and non-comparable. Recall that the production function and hence also the TFP are already estimated sector-specifically due to this concern. Nevertheless, I repeat the entire analysis with manufacturing industries only.

Another reason for caution are the traditionally quite powerful labor unions in Germany. The industry-specific and nationwide valid agreements regulate, among others, the wage and the right of cancellation. A possible consequence of the collective bargaining is that workers' remuneration may not accurately reflect their productivity and, in turn, their quality. However, the collective agreement coverage only applies for union members and upward deviations of the wage are allowed. Despite declining union membership rates over the last few decades, coverage in the data set is still quite large. About 70% of workers are employed in an establishment which is covered by an industry-wide collective

[25] The non-manufacturing industries are the construction, trade and food-service industry.

agreement. Another 9% work for an establishment which reports that it orients itself by these agreements. It will thus be interesting to verify whether the participation of a firm has implications for the calculation of the matching pattern and its strength. To this end, I split the sample into plants with and without collective agreements or orientation on these agreements. Finally, I repeat the entire analysis using a different imputation procedure to recover top-coded wages, as described in footnote 7. To refine the procedure, I estimate the censored regression for all different combinations of years, education groups, gender and East/West separately. One the one hand, this potentially yields a better fit of the predicted wages from the censored regression. On the other hand, it allows for different variances in the 216 distinct groups.

The results of these four robustness checks are provided in tables 7 and 8. For the sake of brevity, I will not include all repetitions of the prior results, but show only the most important findings. The (partial) correlation coefficients in table 7 are positive throughout and have a similar dimension to those before. At the level of employer-employee pairs, some differences to the baseline result emerge for the splitted sample of firms with and without collective agreements. However, the calculation of these correlations at the firm level shows little deviation between the three samples and from the prior number. Because the correlation in the sample of firms without collective agreements at the firm level is higher and at the other observation level it is lower than in the remaining part of the sample in panel 3, it is not possible to judge whether the coverage disguises workers' true productivities or disturbs the matching mechanism.

Table 7: Correlations of TFP

	employer-employee level		firm-year level	
panel 1: manufacturing industries only				
υ_i	0.0965	0.0887	0.1559	0.1335
log density		0.0272		0.0341
panel 2: firms without collective agreements				
υ_i	0.0409	0.0320	0.1857	0.1667
log density		0.0274		0.0326
panel 3: only firms with collective agreements				
υ_i	0.1232	0.0973	0.1724	0.1561
log density		0.1351		0.0626
panel 4: different wage imputation				
υ_i	0.099	0.0730	0.1699	0.1523
log density		0.1335		0.0544

Notes: The cells display (partial) correlation coefficients between worker and firm quality at different observation levels, analog to table 4. All correlations are significant below the 1% level.

Table 8 demonstrates that the wage curve still exhibits a bell-shape in the deviation of the optimal match in all of the four subsamples due to the significant third order term of $\tilde{k}_{ij}$. In fact, the curvature of these estimated lines looks very similar to the one plotted in figure 2. Both results point out that even establishments covered by collective agreements are able to chose workers according to their own TFP and remunerate them according to each worker's own productivity, as is the case in firms without collective agreements. The type of wage imputation procedure is also not decisive for the results. Thus far, the four modifications have corroborated the baseline results. The observed matching pattern in Germany is positive assortative, and a higher concordance of employer and employee quality in a match is accompanied by higher wages.

Table 8: Wages and the deviation from the optimal match

	[1]	[2]	[3]	[4]
k_{ij}	0.0165	0.0222	0.0101	0.0144
	(0.0058)***	(0.0108)**	(0.0034)***	(0.0047)***
k_{ij}^2	-0.0182	-0.0137	-0.0229	-0.0216
	(0.0067)***	(0.0103)	(0.0055)***	(0.0056)***
k_{ij}^3	-0.0096	-0.0110	-0.0083	-0.0087
	(0.0047)**	(0.0043)***	(0.0019)***	(0.0020)***
west	-0.0212	-0.0214	-0.0278	-0.0274
	(0.0072)***	(0.0123)*	(0.0060)***	(0.0070)***
male	-0.0021	-0.0010	-0.0035	-0.0027
	(0.0013)	(0.0024)	(0.0013)***	(0.0013)**
regional controls	✓	✓	✓	✓
constant	-1.4519	-2.1477	-0.9926	-0.6060
	(0.5031)***	(0.5458)***	(0.3600)***	(0.4260)
R^2	0.2509	0.3297	0.3591	0.2578
F	49.88	53.27	48.74	35.45
N	386,378	163,996	469,498	551,047

Notes: The dependent variable is the adjusted log wage rate, as described in the main text. The observation level is employer-employee pairs. Cluster-robust standard errors at the firm-level are in parentheses and significance levels of 0.1, 0.05 and 0.01 are denoted by *, ** and ***, respectively. The number of each column correspond to the four robustness checks as defined in the four panels of table 7.

Finally, I re-estimate the regressions in table 6 to assess the spatial matching pattern in the four subsamples. Like in subsection 4.3, the results do not prove robust. For both matching indicators, the unemployment rate is insignificant and the coefficients indicate that there is a non-linear relation in density, as before. However, only in four of the eight regressions is the significance of the quadratic density term significant below the 10% level.

5 Conclusion

The present study provides robust evidence of positive assortative matching (PAM) in the German labor market. The matching pattern is detected by two different methodologies. On the one hand, the correlation between worker and firm quality is positive in the entire economy. On the other hand, I follow the theoretical instructions in Eeckhout and Kircher (2011) and consider the outcome of single matches. If qualities are complements in the production function, the wage of a given workers exhibits an inverted U-shape in the quality of the employer, having its maximum when both qualities are equal. Because the wage level is not determined by the firm's quality but by the quality of the match, the frequently used firm fixed effects are not a reliable quality measure. The present paper circumvents this problem by using TFP as a direct measure for firm quality. Nevertheless, worker fixed effects capture the labor market value of unobservable adherent skills. Using these two quality measures, the observed wage curve provides a compelling case in favor of PAM. This implies complementarities in the production function and efficiency gains when quality levels are close to each other. A comparison shows that TFP is almost unrelated to the value of firm fixed effects and that the latter depend mainly on the size of the data set.

The paper also demonstrates that it is important to control for agglomeration economies and sorting of skilled agents to densely populated regions. Both are present in the data and without their consideration, the strength of matching is overestimated. The upper bound of wage gains in matches where quality levels are equal is then estimated at 2%, instead of 4%. Taking further advantage of the regional view, I examine if labor market pooling improves the accuracy of matches. In addition to the higher employment density, other possible reasons for lower search costs also imply an increasing local unemployment rate. In the present data, however, both variables can only predict regional differences in matching outcomes to a small extent. Both matching quality indicators show some evidence that matching works best in medium-density counties and indicate no significant relation to the local unemployment rate

References

Abowd, J., Kramarz, F. and Margolis, D. (1999). High wage workers and high wage firms. *Econometrica*, **67** (2), 251–333.

Addison, J. T., Schank, T., Schnabel, C. and Wagner, J. (2006). Works councils in the production process. *Schmollers Jahrbuch*, **126** (2), 251–283.

Alda, H., Bellmann, L. and Gartner, H. (2009). Wage structure and labor mobility in the West German private sector, 1993-2000. In E. P. Lazear and K. L. Shaw (eds.), *The structure of wages: An international comparison*, University of Chicago Press, pp. 261–313.

—, Bender, S. and Gartner, H. (2005). The linked employer-employee dataset created from the IAB establishment panel and the process-produced data of the IAB (LIAB). *Schmollers Jahrbuch*, **125** (2), 327–336.

Andersson, F., Burgess, S. and Lane, J. (2007). Cities, matching and the productivity gains of agglomeration. *Journal of Urban Economics*, **61** (1), 112–128.

Andrews, M., Gill, L., Schank, T. and Upward, R. (2008). High wage workers and low wage firms: negative assortative matching or limited mobility bias? *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, **171** (3), 673–697.

Andrews, M. J., Gill, L., Schank, T. and Upward, R. (2012). High wage workers match with high wage firms: Clear evidence of the effects of limited mobility bias. *Economics Letters*, **117** (3), 824–827.

Baldwin, J. R., Brown, W. M. and Rigby, D. L. (2010). Agglomeration economies: Microdata panel estimates from Canadian manufacturing. *Journal of Regional Science*, **50** (5), 915–934.

Becker, G. (1973). A theory of marriage: Part I. *Journal of Political Economy*, **81** (4), 813–846.

Briant, A., Combes, P. P. and Lafourcade, M. (2010). Dots to boxes: Do the size and shape of spatial units jeopardize economic geography estimations? *Journal of Urban Economics*, **67** (3), 287–302.

Card, D., Heining, J. and Kline, P. (2013). Workplace heterogeneity and the rise of West German wage inequality. *Quarterly Journal of Economics*, **128** (3), 967–1015.

Combes, P., Duranton, G. and Gobillon, L. (2008). Spatial wage disparities: Sorting matters! *Journal of Urban Economics*, **63** (2), 723–742.

Cornelissen, T. and Hübler, O. (2011). Unobserved individual and firm heterogeneity in wage and job duration functions: Evidence from German linked employer-employee data. *German Economic Review*, **12** (4), 469–489.

Delacroix, A. (2003). Heterogeneous matching with transferable utility: Two labor market applications. *International Economic Review*, **44** (1), 313–330.

Duranton, G. and Puga, D. (2004). Micro-foundations of urban agglomeration economies. In V. Henderson and J. F. Thisse (eds.), *Handbook of Regional and Urban Economics*, vol. 4, Amsterdam: NorthHolland, pp. 2063–2117.

Eckey, H.-F., Kosfeld, R. and Türck, M. (2006). Abgrenzung deutscher arbeitsmarktregionen. *Raumforschung und Raumordnung*, **64** (4), 299–309.

Eeckhout, J. and Kircher, P. (2011). Identifying sorting–in theory. *Review of Economic Studies*, **78** (3), 872–906.

Ehrl, P. (2013). Agglomeration economies with consistent productivity estimates. *Regional Science and Urban Economics*, **43** (5), 751–763.

— (2014). Residual wage inequality in Germany. *mimeo*.

Ellison, G., Glaeser, E. L. and Kerr, W. R. (2010). What causes industry agglomeration? Evidence from coagglomeration patterns. *American Economic Review*, **100** (3), 1195–1213.

Fischer, G., Janik, F., Müller, D. and Schmucker, A. (2009). The IAB establishment panel - things users should know. *Schmollers Jahrbuch*, **129** (1), 133–148.

Fitzenberger, B., Osikominu, A. and Völter, R. (2006). Imputation rules to improve the education variable in the IAB employment subsample. *Schmollers Jahrbuch*, **126** (3), 405–436.

Gartner, H. (2005). The imputation of wages above the contribution limit with the German IAB employment sample. *FDZ Methodenreport*, **2/2005**.

Gautier, P. and Teulings, C. (2006). How large are search frictions? *Journal of the European Economic Association*, **4** (6), 1193–1225.

Gibbons, R. and Katz, L. (1992). Does unmeasured ability explain inter-industry wage differentials? *Review of Economic Studies*, **59** (3), 515–535.

Glaeser, E. L. and Gottlieb, J. D. (2009). The wealth of cities: Agglomeration economies and spatial equilibrium in the United States. *Journal of Economic Literature*, **47** (4), 983–1028.

Gruetter, M. and Lalive, R. (2009). The importance of firms in wage determination. *Labour Economics*, **16** (2), 149–160.

Helsley, R. W. and Strange, W. C. (1990). Matching and agglomeration economics in a system of cities. *Regional Science and Urban Economics*, **20** (2), 189–212.

Kawka, R., Beisswenger, S., Costa, G., Kemmerling, H., Müller, S., Pütz, T., Schmidt, H., Schmidt, S. and Trimborn, M. (2009). *Regionaler Preisindex*. Berichte Band 30, Bundesinstitut für Bau-, Stadt- und Raumforschung, Bonn.

Lazear, E. P. and Shaw, K. L. (2009). Wage structure, raises and mobility. In E. P. Lazear and K. L. Shaw (eds.), *The structure of wages: an international comparison*, University of Chicago Press, pp. 1–57.

Levinsohn, J. and Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. *Review of Economic Studies*, **70** (2), 317–342.

Marshall, A. (1890). *Principles of Economics*. London: Macmillan, 1961, 9th edn.

Matthes, B., Burkert, C. and Biersack, W. (2008). Berufssegmente: Eine empirisch fundierte Neuabgrenzung vergleichbarer beruflicher Einheiten. *IAB Discussion Paper*, **35/2008**.

Mion, G. and Naticchioni, P. (2009). The spatial sorting and matching of skills and firms. *Canadian Journal of Economics*, **42** (1), 28–55.

Müller, S. (2008). Capital stock approximation using firm level panel data. *Jahrbücher für Nationalökonomie und Statistik / Journal of Economics and Statistics*, **228** (4), 357–371.

Pissarides, C. A. (2000). *Equilibrium unemployment theory*. MIT Press, Cambridge, 2nd edn.

Postel-Vinay, F. and Robin, J.-M. (2006). Microeconometric search-matching models and matched employer-employee data. In R. Blundell, W. Newey and T. Persson (eds.), *Advances in Economics and Econometrics, Theory and Applications*, vol. Ninth World Congress, Vol. II, Cambridge University Press, Cambridge, pp. 877–907.

Puga, D. (2010). The Magnitude and Causes of Agglomeration Economies. *Journal of Regional Science*, **50** (1), 203–219.

Roback, J. (1982). Wages, rents, and the quality of life. *Journal of Political Economy*, **90** (6), 1257–1278.

Shimer, R. and Smith, L. (2000). Assortative matching and search. *Econometrica*, **68** (2), 343–369.

Van den Berg, G. J. and Van Vuuren, A. (2010). The effect of search frictions on wages. *Labour Economics*, **17** (6), 875–885.

Wheeler, C. (2001). Search, sorting, and urban agglomeration. *Journal of Labor Economics*, **19** (4), 879–899.

A TFP estimation

This section explains how total factor productivity (TFP), the preferred measure of firm quality, is estimated. It is common to assume a Cobb-Douglas production technology which, in its logarithmic form, reads

$$y_{jt} = TFP_{jt} + \alpha_k k_{jt} + \alpha_l l_{jt} + \alpha_m m_{jt} + \zeta z_{jt} + u_{jt} \tag{4}$$

where y_{jt} is the output of plant j in period t, $\alpha_k, \alpha_l, \alpha_m$ are its inputs of capital, labor and material inputs, respectively. z_{jt} represents some additional controls and u_{jt} is the error term. I control for the establishments share of high skilled workers, the number of hours worked per week, year dummies, a dummy for plants in West Germany and whether it is covered by a collective agreement. The empirical realization suffers from not having the output, as in most data sets. It is usual to proxy output by the plant's revenues, which requires the assumption of isomorphic price setting behavior.[26] Another problem is that no information about the capital stock is given in the LIAB data. It is constructed by the use of the perpetual inventory method from plants investments, prevalent with this data, cf. Addison *et al.* (2006). A modified version of the standard perpetual inventory method according to Müller (2008) is applied here.[27] To overcome the endogeneity of the input factors, Levinsohn and Petrin (2003) propose an estimation method, where the unobserved productivity in equation (4) is proxied by a polynomial in the intermediate input usage. The idea is that as input use depends on the current productivity level and the capital stock, the inversion of this function, $m_{jt}(TFP_{jt}, k_{jt})$, allows leaving the unobserved TFP_{jt} and thereby the endogeneity problem out of the equation. Because the polynomial generates multicollinearity with the primary capital and intermediates input, their identification is prevented in the first stage of the estimation. Consequently, α_k and α_m are identified from the estimated polynomial in a second stage. The exact transformation and reasoning is more complex and the reader is therefore referred to Levinsohn and Petrin (2003). Estimation departs from the authors' approach, in that all variables are interacted with sector dummies. Consequently, the production function is sector-specific and thus far more accurate than assuming a single production function for all establishments. Note that the production function is estimated from all plants with complete information in the data and not only those that are included in the LIAB sample. Furthermore, I use the weights provided in the establishment panel to make the TFP estimates representative for the entire population. The exact coefficient estimates are of minor importance here, but are available upon request from the author. After obtaining all coefficients, TFP is residually computed and normalized to have a mean of zero in each sector. That is, the TFP represents the deviation from the average productive establishment in a sector.

[26] See Ehrl (2013) for a more data demanding but more accurate approach to remedy this possible price bias.

[27] This method differs in the construction of the starting value for the perpetual inventory method. The starting value is calculated as the time-mean of replacement investments divided by a sector-specific depreciation rate.