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TFP, Labor Productivity and the (un)observed labor input: temporary agency work

Alexander Schiersch*

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Abstract

The study focuses on the question of whether or not productivity estimates are biased due to the emergence of a new input that is usually omitted: temporary agency worker (TAW). The study analyzes labor productivity and TFP by means of a structural approach using a representative dataset of German manufacturing firms. The empirical results show, once TAW is taken into account, that: i) labor productivity in most manufacturing sectors is significantly lower; ii) average TFP differs significantly in most sectors; but iii) the coefficients for regular labor are not significantly different between estimations with and without TAW.

Keywords: temporary agency work, total factor productivity, labor productivity, omitted variable bias, structural productivity estimation

JEL Classification: D24, J24, L24, L60

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1. Introduction

Across Europe, atypical forms of employment are becoming increasingly important. Since the mid-1990s, the share of temporary employment has increased significantly, making up about 14 percent of total employment across the Europe Union in 2014.[1] However, the importance of temporary employment varies widely, not just between countries but also between industries within the same economy (Ortega & Marchante, 2010). In some countries, like Poland and Spain, about a quarter or a third of all dependent employees work with temporary contracts. Even in countries like Italy, Germany and France, the proportion of atypical employment is between 13 percent and 15 percent. When focusing on temporary agency workers (henceforth TAW) as a subgroup of atypical employment, the shares are significantly smaller, but temporary agency work has also developed dynamically. In the United Kingdom, more than 1 percent of the total workforce was employed by temporary agency firms in 2011 (Bryson, 2013). In Germany, the share is even higher: 2.9 percent of all employees subject to social security deductions in 2014 are TAW. This corresponds to about 850,000 workers and is more than 5 times greater than it was in the late 1990s.[2]

The growing importance of TAW is inspiring a large and growing literature on the different aspects of temporary agency work. *Inter alia*, several studies show that there is a significant wage gap between TAW and regular employees, albeit varying in size (Jahn, 2010; Antoni & Jahn, 2009; Ford & Slater, 2008; Ford, et al., 2008; Oberst, et al., 2008; Houseman, et al., 2003; Jahn & Rudolph, 2002). This points to potential cost savings for firms, often seen as the main incentive to use TAW (Bryson, 2013; Heywood, et al., 2011; Kleinknecht, et al., 2006; Houseman, et al., 2003). Some studies show, however, that cost savings are not often achieved (Kleinknecht, et al., 2006; Houseman, 2001; Nollen, 1996). Regardless of the cost aspect, the enhanced flexibility is considered to be another advantage of this new type of labor, with stricter employment protection legislation seeming to foster demand for TAW (Heywood, et al., 2011; Vidal & Tigges, 2009; Shire, et al., 2009; Nunziata & Staffolani, 2007; Pfeifer, 2005; Autor, 2003; Booth, et al., 2002a; Houseman, 2001; Bentolila & Saint-Paul, 1992). The possibility to use temporary agency work as an additional probationary period to search for the most productive and best-fit employees is also regarded as beneficial for firms (Beckmann & Kuhn, 2012; Buddelmeyer & Wooden, 2011; Addison & Surfield, 2009; Engellandt & Riphan, 2005; Booth, et al., 2002b; Wang & Weiss, 1998).

However, TAW usage does not come without drawbacks for firms. The use, especially the excessive use of temporary agency work, may result in the morale of all workers, both temporary and permanent, declining (DeCuyper, et al., 2008; Goerge, 2003). The resulting “low levels of job satisfaction and morale may exert an adverse influence on productivity levels” (Brown & Sessions, 2005, p. 311). Additionally, firm-specific human capital of TAW is usually lower than that of permanently employed workers and, due to the short term nature of temporary agency work, TAW receive little, if any, training (Mitlacher, 2008; Zwick, 2006; Albert, et al., 2005; Booth, et al., 2002b; Nollen, 1996). This may also negatively affect the average productivity of firms using TAW.

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[1] Numbers are taken from the *Labour Force Statistics* of the OECD. http://stats.oecd.org/Index.aspx?DatasetCode=TEMP_I#; last accessed: 21.10.2015.

[2] In some professions, for instance *transport and logistics*, the share of temporary agency workers in employment reaches 25 percent (Bundesagentur für Arbeit, 2015).

There is, however, limited literature analyzing the effect of temporary agency work on firm performance; e.g. on productivity, on sales, or other indicators of firm performance. This is because "data on TAW is absent from most data sets" (Bryson, 2013, p. 133). The results of the relevant studies are mixed. Arvanitis (2005) and Kleinknecht, et al. (2006), using data for Swiss and Dutch firms, find no effect of TAW on labor productivity, sales growth, or employment growth. Bryson (2013), on the other hand, finds a significant positive correlation between the use of TAW and the financial performance of British firms. The studies of Beckmann and Kuhn (2009) and Hirsch and Müller (2012) point to a non-linear relationship between output and TAW usage in German plants. In contrast, Diaz-Mayans and Sanchez (2004) and Ortega and Marchante (2010) find evidence for a negative relationship between the use of temporary agency work and labor productivity for Spanish manufacturing firms. Finally, Addessi (2014) finds that TFP growth of Italian manufacturing firms slows when temporary agency work is used.[3]

Hence, the literature on the relationship between firms and TAW usage is not only limited but the findings are ambiguous. In addition, there is virtually no study on another question that is becoming increasingly relevant as TAW is increasingly used by firms: Are the productivity estimates of firms and sectors biased when TAW, as additional labor input, is ignored?

This study aims to address this gap, making two contributions: First, it contributes to the emerging literature on the effect of atypical employment on firm performance using data for German manufacturing firms while utilizing a structural approach. The results indicate that the use of temporary agency work often positively affects firm performance. Second, it provides evidence for biased estimates of sector productivity and firm productivity if TAW, who inherently belong to the labor input, are omitted. Thereby the results also indicate that productivity of German manufacturing sectors, calculated by means of official data, are most likely inaccurate.

The paper is organized as follows. Section 2 discusses the data situation. The model is presented and the hypothesis is developed in section 3. This section also presents and discusses the econometric approach. Section 4 introduces the firm level data, while the results of the analyses are the subject of section 5. Section 6 sums up and discussion the impact of the results.

2. Data Situation

The topic of this study is only relevant if two preconditions are met: (i) if TAW are not included in statistics as employees in the customer firms; and (ii) if temporary agency work significantly affects firm performance. The second prerequisite is left to be tested in the empirical part of this paper. However, a considerable number of studies find significant effects of TAW, both positive and negative. From this we conclude that the literature provides some evidence that the second prerequisite for the research question of this study is fulfilled: the use of TAW most likely affects firm performance.

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3 Each paper is presented in more detail in section A in the appendix. This study deviates from the previous studies in four ways: First, it uses a dataset with more than 125,000 observations that, in contrast to previous German studies, observes TAW usage over the course of the entire year and focuses on firms instead of plants. Secondly, this study applies latest econometric developments, namely a structural approach along the lines of ACF, to estimate the production function. Thirdly, we recognize that the production function might not only differ between manufacturing and service industries, but even within the manufacturing industry. Consequently, the analysis is conducted separately for each two-digit manufacturing sector. Finally, our main focus is on the question whether TAW is a relevant input factor and whether its omission biases productivity estimates as well as the coefficients of labor and capital. This is not previously studied.

To address the first prerequisite, we examine the data situation with respect to German manufacturing companies. In particular, the focus is on the question of whether TAW are included as labor input in firms, either explicitly or implicitly, in the official statistics.

Within Germany, the *Federal Employment Agency (Bundesagentur für Arbeit - BA*) is, *inter alia,* responsible for collecting data and providing statistics on employment and other labor market related issues. The two main statistics provided by the BA and relevant for the research question are the *statistic on employees with social security contributions and minor employment* (short: *employment statistic*) and the *statistic on temporary employment*.

The *employment statistic* contains three variables relevant for the topic of this paper: occupation, industry (classification system WZ 2008), and place of work.[4] Thus, the *employment statistic* provides information on the number of employees in each industry. But because TAW are hired by temporary work agencies, they are counted as employees in industry *N78 - Employment activities*. In addition, the workplace is the seat of the respective subsidiary, branch or headquarters of the temporary employment agency, not the actual location of the customer. Because of that, the *employment statistic* provides no information about the TAW input in any industry other than sector *N78* (Biehler, 2011). The *statistic on temporary employment* contains three similar variables that are relevant for the issue at hand: occupation, previous occupation and federal state.[5] The assignment to a federal state depends on the location of headquarters of the temporary work agency (Biehler, 2011). Occupation allows only general inferences on the client industries that most likely use such occupations. However, we are forced to guess whether an electrician works in a manufacturing firm, in a real estate company, or in a construction firm. Hence, we cannot use occupational information to assign TAW unequivocally to a specific industry, in particular not at the two-digit industry level. Consequently, both BA-statistics relevant to the research question contain no information about the customer firms or information about the industries of the customer firms. Finally, the *Federal Employment Agency* confirms, on request, that statistics incorporating information about the number of TAW in specific firms or industries do not exist, at least not as of 2015.

The second source for official data on firms and employment are the datasets of the German *Federal Statistical Office* and the *Statistical Offices of the States*. The datasets of the statistical offices are also supplied to supranational organizations and institutions, such as the *OECD* or *Eurostat,* and are the source of the German data in those datasets. The subsequent list of datasets is limited to those for manufacturing firms because the analysis will focus on these firms for data availability reasons.

The only business cycle survey for the manufacturing industry that includes information on employment is the *monthly report in the manufacturing sector*.[6] It contains the following labor related variables: number of employees; gross wages; and hours worked (Statistisches Bundesamt, 2015b). The

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[4] The full list of variables is: sex; age; nationality; training; occupation; position in the company; full / part-time employment; industry (classification system WZ 2008); pension insurance; average monthly wage is within the interval 450-850 euros; place of work; home address; and gross wage (Bundesagentur für Arbeit, 2014b).

[5] The full list of variables is: sex; nationality; occupation; previous occupation; job duration (with employment agency); operating purpose of employment agency; and federal state (Bundesagentur für Arbeit, 2013).

[6] The remaining business cycle surveys are: *quarterly production survey in the manufacturing sector*; *indices of new orders in the manufacturing sector; indices of turnover in the manufacturing sector*; *indices of production in the manufacturing secto*r; and *indices of labor productivity in the manufacturing sector*. These surveys and indices contain no information about employment. The indices for labor productivity are based on the *monthly report in the manufacturing sector* and the *production survey*.

structural business statistics include the *investment survey in the manufacturing industry*, the *annual report for establishments in the manufacturing industry,* and the *cost structure survey in the manufacturing industry*. The only labor related variable recorded in the *investment survey in the manufacturing industry* is number of persons employed (Statistisches Bundesamt, 2013). The *annual report for establishments in the manufacturing industry* includes the following labor related variables: persons employed and sum of gross salaries (Statistisches Bundesamt, 2012). Finally, the *cost structure survey in the manufacturing industry* contains, *inter alia,* the number of persons employed; total gross wages; number of owners working in the firm; number of trainees; number of part-time workers; female employees; other social security costs; and costs for temporary agency workers (Statistisches Bundesamt, 2015a). The latter variable is a key variable for the analysis and is discussed in detail in section 4. The metadata for all listed datasets explicitly state that TAW shall not be included in the number of persons employed and that expenditures on TAW shall not be included in the data about wages and wage related costs. This and the listed variables for each dataset show that the different datasets of the statistical offices do not provide information about the number of TAW used by firms or about the hours worked by TAW.

In sum, the metadata of the various statistics reveal that the first prerequisite for the hypothesis holds: the number of TAW is not included in any official statistics that provide employment numbers for German industries.

3. Model and Estimation Strategy

Model and Hypothesis

In order to estimate TFP as well as the coefficients for TAW and regular employment, we modify the model of Haskel and Martin (1993). It was originally developed to account for the effect of skilled and unskilled labor in estimating productivity. Hence, we start with a standard Cobb-Douglas production function (for a single firm at time t):

$$Y = N^{\alpha} K^{\beta} e^{\omega} \tag{1}$$

where N is the effective labor input, K is effective capital input and ω is total factor productivity. Following Haskel and Martin (1993), we assume that the relationship between L_T and L_P is of multiplicative nature,[7] defining effective labor input as $N = L_T^{\theta} L_P^{\gamma}$, where L_T represents the labor input of temporary agency workers and L_P the input of employees with a permanent contract. If we assume that there is at least one permanent employee in each firm, the relationship between L_T and L_P can be described by $s_n = L_T / L_P$ or $L_T = s_n L_P$ with $s \geq 0$. How to estimate the share from real data without knowing L_T is discussed in section 4 and the appendix. The estimation function is derived by substituting N into Eq. (1) and taking logarithms:

$$y = \alpha_1 l_T + \alpha_2 l_P + \beta k + \omega \tag{2}$$

[7] This assumption is used explicitly or implicitly in other studies, e.g. in Sala and Silva (2013), who analyzes the effect of vocational training on labor productivity; in Hirsch and Müller (2012) on the relationship between TAW and output of German plants; in Ortega and Marchant (2010) on the effect of TAW on labor productivity in Spain; and in Doraszelski and Jaumandreu (2013), who analyze the effect of R&D on productivity.

with $\alpha_1 = \alpha\theta$ and $\alpha_2 = \alpha\gamma$.

Looking at the research question of this study, Eq. (2) indicates the problem. Rearranging it shows that TFP is a sort of residual or an intercept. If temporary agency work is ignored, the entire term $\alpha_1 l_T$ is added to the TFP and may bias the estimated TFP, i.e. $\omega + \alpha_1 l_T = y - \alpha_2 l_P - \beta k$. But TFP is not necessarily upward biased if TAW is ignored. This follows from the fact that the coefficient for each control variable is defined not only by the relationship between the respective variable and the dependent variable but also by the relationships among the independent variables.

To demonstrate this, we use at the log of Eq. (1) and ignore for a moment the question of how to define *n*. This helps to overcome the problem that, "it is generally impossible to sign the biases of the OLS coefficients in a multivariate context," as noted by Levinsohn and Petrin (2003, p. 319). Thus, the function we look at for a moment is $y = \omega + \alpha n + \beta k$. The two coefficients and the productivity are estimated by OLS as follows:

(3) $$\hat{\alpha} = \frac{\sigma_{kk}\sigma_{ny} - \sigma_{nk}\sigma_{ky}}{(\sigma_{nn}\sigma_{kk} - \sigma_{nk}^2)} \;;\; \hat{\beta} = \frac{\sigma_{nn}\sigma_{ky} - \sigma_{nk}\sigma_{ny}}{(\sigma_{nn}\sigma_{kk} - \sigma_{nk}^2)} \;;\; \hat{\omega} = \bar{y} - \hat{\alpha}\bar{n} - \hat{\beta}\bar{k}$$

where σ_{nk} denotes the sample covariance between n and k and σ_{nn} the variance of n etc. If the estimation is conducted while ignoring the relevant input k, the coefficient α would be biased in the following way:

(4) $$\breve{\alpha} = \hat{\alpha} + \hat{\beta}\frac{\sigma_{nk}}{\sigma_{nn}}$$

This equation shows, as long as the covariance between the two input factors is positive and β is positive, that such estimation would result in an upward biased estimate for α, because σ_{nn} is always positive. The coefficient for n would be underestimated if the covariance between the two variables is negative and if β remains positive. $\breve{\alpha}$ is only unbiased when $\sigma_{nk} = 0$ or when β is not significantly different from zero. The distortion would of course also affect ω, as seen in the last equation in Eq. (3). In fact, $\hat{\omega}$ would be downward biased if $\breve{\alpha}$ is sufficiently upward biased.

In other words, when considering the existence of a third omitted input in a production function with labor and capital, the coefficients of labor or capital will be biased if one of these two variables is sufficiently correlated with the omitted variable and as long as the omitted variable is a relevant input factor. As a consequence, the TFP estimate will also be biased. However, the direction of the bias cannot, *a priori,* be determined. It depends on the relationship among the independent variables as well as between the dependent variable and the independent variables. Moreover, it remains to be seen whether the differences between the "true" and the "biased" coefficient is large enough to be statistically significant.

Given the mathematical relationship between the unobserved and the observed variables, given that the literature often finds a significant effect of temporary agency work, and given the omission of TAW from statistics on employment within manufacturing companies, we postulate the following hypothesis:

> Productivity estimates of German manufacturing firms and industries are biased due to the omission of a part of the labor input: the temporary agency workers.

Econometric approach

We apply a structural approach for estimating TFP and the input coefficients of Eq. (2) These approaches are introduced by Olley and Pakes (1996) (henceforth OP) and further improved by

Levinsohn and Petrin (2003) (henceforth LP) and Ackerberg, Caves and Frazer (2006) (henceforth ACF). The starting point for the discussion is the ACF approach, which we expand so that the elasticity of temporary agency work can be consistently estimated.

However, let us start with concisely summarizing the ACF approach. The general idea of the structural approaches is to use a function of observables to approximate the unobserved firm productivity (ω_{it}). This helps overcome the endogeneity problem that, if ignored, leads to biased coefficients for labor and capital (Ackerberg, et al., 2007). Within the ACF framwork, we assume that, *inter alia*, a function for intermediate input demand exists $\left(m_{it} = f(l_{it}, k_{it}, \omega_{it})\right)$ that is strictly monotonic in ω_{it}; and ω_{it} is the only unobserved state variable in that function (Ackerberg, et al., 2006). Due to this assumption, the intermediate input function is invertible and it is possible to substitute it into the production function for the unobserved productivity (ω_{it}). The coefficients for labor and capital are then consistently estimated within the two step procedure subsequently presented. The merit of ACF is to show that if labor is a completely variable input and chosen simultaneously with material, a collinearity problem exists, thus making it impossible to derive consistent estimates for the labor coefficient. In the context of the ACF approach, this problem is resolved by making labor less variable than material, which is achieved by changing the timing assumption for labor.

With the ACF setting as starting point, we can develop the estimation procedure for a production function that includes temporary agency work as a third input factor (see Eq. (2)). This requires clarifying how the coefficient of TAW can be consistently estimated and whether TAW has to enter the control function for ω_{it}. It is clear that TAW is a variable and non-dynamic input. This is, after all, the main feature of this input factor. In this respect, TAW is almost no different from material. We could therefore assume that $l_{T,it}$ it is chosen simultaneously with m_{it}. Consequently, the function for $l_{T,it}$ depends on the same variables as the function for m_{it}:

(5) $$l_{T,it} = h_t\left(\omega_{it}, k_{it}, l_{P,it}\right);\ \ m_{it} = f_t\left(\omega_{it}, k_{it}, l_{P,it}\right).$$

Given that $\omega_{it} = f_t^{-1}\left(k_{it}, m_{it}, l_{P,it}\right)$, we can rewrite the equation for $l_{T,it}$ by substituting ω_{it} and it becomes immediately obvious that $l_{T,it}$ depends not only on labor and capital but also on the decision for m_{it}, i.e.

(6) $$l_{T,it} = h_t\left(f_t^{-1}\left(k_{it}, m_{it}, l_{P,it}\right), k_{it}, l_{P,it}\right).$$

Thus, the coefficient for $l_{T,it}$ cannot be consistently estimated due to collinearity between $l_{T,it}$ and the non-parametric function f_t^{-1}. This collinearity arises from the fact that the variables that can describe the variation of $l_{T,it}$ are also included in f_t^{-1}, which is used to approximate ω_{it}.

To resolve the issue, we use the reasoning of ACF to overcome the collinearity problem of $l_{P,it}$. Hence, we avoid the simultaneity issue and break the collinearity problem by minimally changing the point in time when the firm decides about $l_{T,it}$. Let us assume that $l_{T,it}$ is chosen at $t-g$, after $l_{P,it}$, which is decided upon at $t-b$ (Ackerberg, et al., 2006), but before m_{it}, with $t-1 < t-b < t-g < t$ and $0 < g < b < 1$. Consequently, $l_{T,it}$ no longer depends on the decision for m_{it}. The material demand function, on the other hand, now also depends on the decision about the use of TAW, becoming

(7) $$m_{it} = f_t\left(\omega_{it}, k_{it}, l_{T,it}, l_{P,it}\right)$$

As in LP, and ACF, we continue to assume that the material input function is strictly monotonic and ω_{it} is the only unobserved state variable. This allows for ω_{it} to be inverted out, which is then described by

$\omega_{it} = f_t^{-1}(m_{it}, k_{it}, l_{T,it}, l_{p,it})$. Substituting ω_{it} into the above outlined production function (Eq. (2)) leads to

(8) $$y_{it} = \varphi_t(k_{it}, m_{it}, l_{T,it}, l_{P,it}) + \varepsilon_{it},$$

where $\varphi_t(k_{it}, m_{it}, l_{T,it}, l_{P,it}) = \alpha_1 l_{T,it} + \alpha_2 l_{P,it} + \beta k_{it} + f_t^{-1}(k_{it}, m_{it}, l_{T,it}, l_{P,it})$. $f_t^{-1}(k_{it}, m_{it}, l_{T,it}, l_{P,it})$ is non-parametrically approximated by a polynomial of order two or more in the four variables (Ackerberg, et al., 2007). As in the original ACF approach, Eq. (8) is estimated in the first step of the estimation procedure by means of OLS. The variables $l_{T,it}$, $l_{P,it}$ and k_{it} have to enter $\varphi_t(k_{it}, m_{it}, l_{T,it}, l_{P,it})$ because they are collinear with f_t^{-1}, as they are part of f_t^{-1}, and, therefore, are not identified in this first step of the estimation routine. The identification of α_1, α_2 and β takes place in the second step.

That second step utilizes the assumption that ω_{it} follows a first-order Markov process (Olley & Pakes, 1996; Levinsohn & Petrin, 2003; Ackerberg, et al., 2006). Hence, the firm's expectation about its productivity depends on its experienced past productivity, formally $\omega_{it} = E(\omega_{it}|I_{it-1}) + \xi_{it} = E(\omega_{it}|\omega_{it-1}) + \xi_{it}$, where I_{it-1} is the information set that contains all past information, and ξ_{it}, which is the "innovation" component that is independent of all past information (Ackerberg, et al., 2007). This can be rewritten as an AR(1) process $(\omega_{it} = g(\omega_{it-1}) + \xi_{it})$. Following Petrin, Poi and Levinsohn (2004), this AR-process can be approximated non-parametrically by

(9) $$\omega_{it} = \lambda_0 + \lambda_1\omega_{it-1} + \lambda_2\omega_{it-1}^2 + \lambda_3\omega_{it-1}^3 + \epsilon_{it}.$$

Finally, it follows from $\omega_{it} = f_t^{-1}(k_{it}, m_{it}, l_{T,it}, l_{P,it})$ and $\varphi_t(k_{it}, m_{it}, l_{T,it}, l_{P,it}) = \alpha_1 l_{T,it} + \alpha_2 l_{P,it} + \beta k_{it} + f_t^{-1}(k_{it}, m_{it}, l_{T,it}, l_{P,it})$ that $\omega_{it} = \varphi_{it} - \alpha_1 l_{T,it} - \alpha_2 l_{P,it} - \beta k_{it}$. This last equation can be substituted into Eq.(9), which is then estimated as second step in the estimation routine. GMM is used to obtain the coefficients for capital and the two types of labor in this second stage.

In order to consistently estimate these coefficients, capital and labor must be orthogonal to ξ_{it}, which is included in ϵ_{it}. This is ensured by the different timing assumptions. Since the seminal study of OP it is assumed that the capital stock k_{it} is determined by the capital stock in $t-1$, k_{it-1}, and the investment (i_{it-1}) in $t-1$. In other words, k_{it} is determined by the information set in $t-1$, but not by the information available in t. Because of this timing assumption, k_{it} is independent from the unexpected innovation shock ξ_{it} and the moment condition $E[\xi_{it}|k_{it}] = 0$ can be used to estimate β (Ackerberg, et al., 2006).

As briefly addressed above, the timing decision for labor is different, which also requires a different moment conditions. Within the ACF framework, the decision on labor input is taken after $t-1$, at $t-b$ $(0 < b < 1)$, but before the decision on material at t. Nevertheless, $l_{P,it}$ "will generally be correlated with at least parts of ξ_{it}. On the other hand, lagged labor, $[l_{P,it-1}]$, was chosen at time $t-b-1$. Hence it is in the information set I_{it-1} and will be uncorrelated with ξ_{it}" (Ackerberg, et al., 2006, p. 19). It follows that lagged labor should be used in the moment condition $(E[\xi_{it}|l_{P,it-1}] = 0)$ to identify α_2. However, ACF also point out that $l_{P,it}$ can be used instead of $l_{P,it-1}$, when it is reasonable to assume that it is not completely variable and is rather "chosen at or prior to $t-1$…. This is likely to generate more efficient estimates than the moment condition using $[l_{P,it-1}]$" (Ackerberg, et al., 2006, p. 21). Assuming that $l_{P,it}$ is chosen at $t-1$ might be reasonable if adapting the core workforce needs time (Ackerberg, et al., 2006). Given the rigid labor market conditions and the strict employment protection legislation in Germany, firms are rather reluctant to alter their core workforce on short notice. Instead, they increasingly use TAW as a tool to adjust employment to product demand fluctuations and for capacity adjustments. In fact, this was one of the exact aims of a series of German labor market reforms in 2004, the so called *Hartz* reforms: to ease the use of short-term employment, temporary agency work and similar forms of atypical employment, so that a portion of a firm's workforce is flexible such that labor input can easily be increased or reduced depending upon the firm's individual situation. At the same time, however, the level of protection for employees with a regular contract remained high. Therefore, we follow ACF and assume that the decision on labor input for t is taken in $t-1$. Consequently, the appropriate moment condition is $E[\xi_{it}|l_{P,it}] = 0$.

A third moment condition is needed to identify the coefficient for temporary agency work in the second stage of the process. $l_{T,it}$ cannot be used as it is partly correlated with ξ_{it} due to the timing assumption. At the same time, $l_{T,it-1}$ is in the information set I_{it-1}, which makes it independent of ξ_{it}. Therefore, once lagged temporary agency work can be used as moment condition in the second stage. Summing up, the following moment-conditions allow identifying the coefficients for capital, permanent labor and TAW:

(10) $$E\left[\xi_{it}\middle|\begin{matrix} l_{P,it} \\ l_{T,it-1} \\ k_{it} \end{matrix}\right] = 0$$

The estimation is conducted for the German manufacturing sector as a whole and for each two-digit manufacturing industries separately. Thus we take into account: (i) that the production functions might differ between manufacturing industries, which also means that the coefficients are different; and (ii) that the intensity of TAW usage differs between sectors and consequently the potential bias will differ too. In addition, performing the analysis on two-digit sector level also serves as a robustness test.

4. Data and Descriptive Statistics

The firm level analysis is conducted using annual data from the German *cost structure survey* of manufacturing firms (CSS). The CSS is compiled by the German *Federal Statistical Office* and firms are legally obliged to provide the requested data. All companies with more than 500 employees are covered by the survey. In addition, smaller firms, with 20 to 500 employees, are included via random subsamples that are designed to be representative at the two-digit sector level and at state level. These subsamples remain constant for four years.[8] The data is confidential, but accredited researchers can apply for data usage. The analysis is performed through remote data processing.[9] The dataset contains, *inter alia*, data on gross value added (Y) that is used as output, material (M) that is used as an instrument, and the number of persons engaged (L_p) as permanent labor. The capital stock (K) is constructed using the method that Wagner (2010) proposes for this dataset.[10]

The unprocessed sample used in this study covers the 2003 to 2011 period. It contains 143,694 observations. After an initial data cleaning in which firms with no industry classification, no employees, no value added, or no capital, etc. are dropped form the dataset, the number of observations is 130,246. Most of the deleted observations lack industry classifications or capital data. In a second

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8 For more information about the dataset see Fritsch, et al. (2004).

9 For more information see Zühlke et al. (2004) and http://www.forschungsdatenzentrum.de/en/data_access.asp.

10 Table D-5 in the appendix provides the descriptive statistics for these variables.

step, we identify all observations with values below the 0.5 percentile or above the 99.5 percentile variable by variable and drop those observations that are above or below the threshold as potential outliers. This reduces the number of observations to 125,977. We also drop the observations of sectors ISIC 12 (m*anufacturing of tobacco products*) and ISIC 19 (*manufacture of coke and refined petroleum products*) due to a lack of observations and potential violation of the privacy policy rules of the statistical offices.[11] This reduces the number of observations to 125,526.

The dataset contains the variable *cost for temporary agency worker,* which is extremely important for the analysis. According to the metadata, this "includes only the cost for employees, who have been rented from employment agencies for money in accordance with the Employment Act to perform work within the firm."[12] Hence, the variable is only different from zero if a firm has used TAW at some point within a calendar year and paid for them. The dataset also contains information on costs for regular employees. The CSS metadata emphasize that data on regular employment does not include TAW.[13]

This information is used for two purposes. First, a non-zero observation in the variable *cost for temporary agency worker* shows that a firm has made use of TAW. Hence, we know how many firms have, at some point within a year, actually used TAW. Second, we can calculate the cost share $(s_{c,it})$ using the observed costs for permanent employees $(C_{P,it})$ and the costs for temporary agency $(C_{T,it})$. This cost share can then be used to approximate the number of TAW per firm $(L_{T,it})$ from the following relationship: $L_{T,it} = L_{P,it} s_{c,it}/d$, while d is an adjustment factor measuring the differences in costs for TAW compared to employees with a permanent contract.[14] Hence, although the number of employees in official firm statistics does not include TAW, we can use information on costs to approximate the number of TAW and conduct the analysis. However, this procedure requires an assumption about the discount factor d.

It is often observed that TAW earn less than their colleagues with open-end contracts (Jahn, 2010; Antoni & Jahn, 2009; Ford & Slater, 2008; Houseman, et al., 2003; Jahn & Rudolph, 2002). However, this does not necessarily mean that the costs for the customer firms are lower when they use TAW instead of permanent employees. Indeed, some studies show that companies see limited savings due to the actual fee they have to pay to the temporary work agencies (Kleinknecht, et al., 2006; Houseman, 2001; Nollen, 1996). Such fee not only includes the gross wages of the temporary agency workers, but it also covers the costs, risks and profits of the temporary employment agencies (Kvasnicka, 2005).

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[11] Both sectors have very few observations (159 observations from 21 firms in ISIC 12 and 292 observations from 47 firms in ISIC 19). Once we focus on firms that use TAW, only 12 firms in sector ISIC 12 and 25 firms in sector ISIC 19 remain. This leads to conflicts with statistical office privacy policies. In addition, these two sectors are atypical for the manufacturing sector, because production mainly takes place abroad while primarily headquarter activities are located in Germany. Labor productivity of these two sectors is, consequently, on average 3 times larger than the average of all other manufacturing sectors.

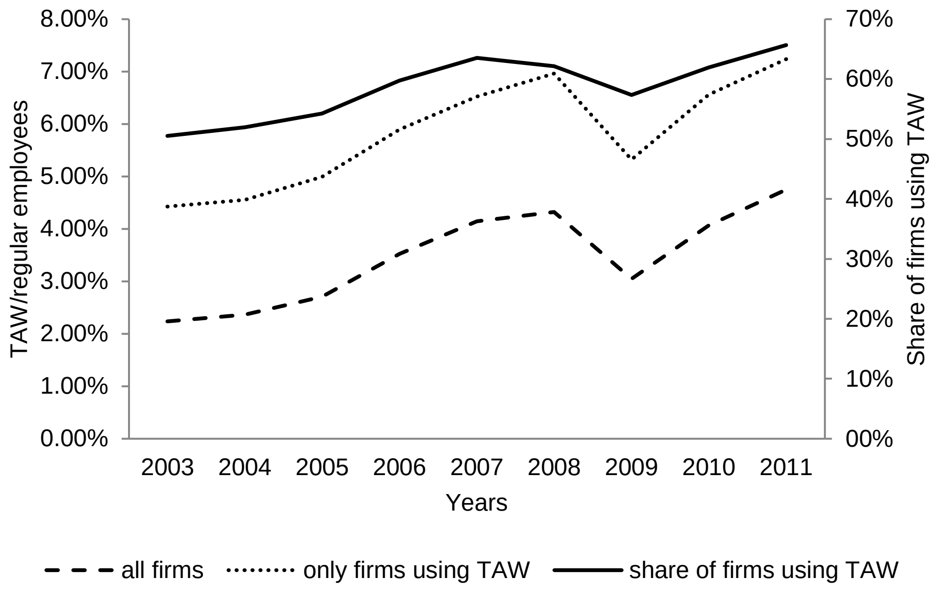
[12] The precise term in the questionnaire is "Kosten für Leiharbeitnehmer/-innen" The original explanation in the meta data is: "Hierzu zählen nur die Aufwendungen für Arbeitskräfte, die von Arbeitsvermittlungsagenturen u. ä. Einrichtungen gegen Entgelt zur Arbeitsleistung gemäß dem Arbeitnehmerüberlassungsgesetz überlassen wurden" (Statistisches Bundesamt, 2015a, pp. 11,15).

[13] In the category "labor costs" for example, it is emphasized that firms should not include any TAW expenditures: "Nicht einzubeziehen sind Beträge, die für Leiharbeitnehmer/Leiharbeitnehmerinnen gezahlt werden…" (Statistisches Bundesamt, 2015a, p. 15).

[14] For a more detailed discussion on how to derive the number of TAW from cost data and on the discount factor d, see section B in the appendix.

We make use of these insights to derive an qualified estimate about the discount factor d. As discussed in detail in the appendix, the "true," but unknown, discount factor is somewhere between 0.5 and 1.5. These upper and lower limits are calculated using the findings in the literature on wage gaps as well as the difference between gross wages of TAW and the fees that temporary work agency charge. As also shown in the appendix, it is reasonable to assume that the overall costs for hiring temporary workers are almost equal to the gross wage costs for permanent workers $(d = 1)$. It should be noted that this initial assumption of equal costs is very conservative in the context of this study. If the costs for a TAW would for example only be half as much as that of a permanent employee $(d = 0.5)$, one could actually hire two TAW for the same cost as one permanent employee. In other words, assuming lower costs per TAW increases the number of TAW, given the observed costs for TAW in the data. This would make it actually easier to find differences, at least in labor productivity.

Figure 1: TAW usage by German manufacturing firms $(d = 1)$



Source: *cost structure survey*; own calculations.

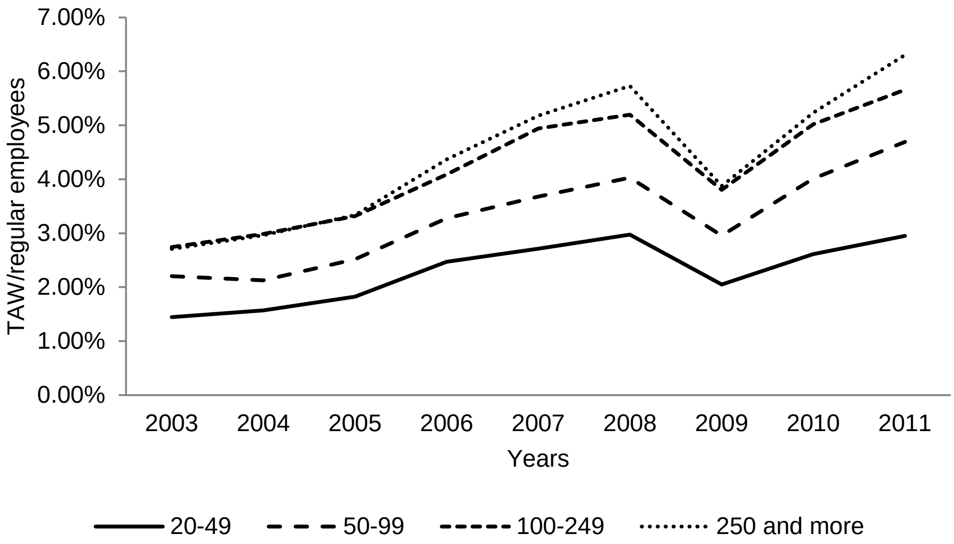
Figure 1 provides first evidence about the use of temporary agency work by companies. The solid line indicates the share of firms in the dataset that used TAW between 2003 and 2011. The dotted lines show the average ratios of TAW to regular employees, calculated as described above, for all firms and for the subset of firms that used TAW in each respective year. The figure reveals that temporary agency work is heavily used by German manufacturing firms. In 2003 half of all companies in the dataset used TAW at some point. This share increased almost continuously to over 65 percent in 2011.[15]

[15] This is a marked difference in comparison to the study by Hirsch and Müller (2012). The share of TAW user plants is only around 2.5 percent in 2008 in their dataset. There are three factors explaining this difference: First, the observation unit in the IAB survey is the plant, not the firm, and there are significantly more plants than firms. Second, the dataset analyzed in Hirsch and Müller (2012) includes plants from multiple sectors: the *manufacturing, trade and repair, transport and communication, industrial services (excluding real-estate activities),* as well as *hotels and restaurants*. Third, and most likely the main reason, is the difference in the reference period between the two sources. The IAB Survey focuses on the presence of TAW in a plant on one specific day in the year: June 30th. The CSS instead asks for expenditures for TAW throughout the entire year.

The intensity of the usage by the firms also increased. The average ratio of temporary agency workers to core workforce grew from 2.2 percent in 2003 to 4.8 percent in 2011 for all firms and from 4.4 percent to 7.2 percent in the subset of firms that used TAW. The drop in 2009 was due to the global recession in the aftermath of the Lehman shock. Here the companies made use of the flexibility that temporary agency work provides by adjusting labor input to meet reduced demand. Summing up, Figure 1 reveals that TAW usage grew at both the extensive and intensive margin.

The average ratio of TAW to regular employees ranges from 0.45 to 8.5 percent in the different industries.[16] With a range from 2.2 to 12.8 percent, the average ratios are higher when focusing only on those observations where TAW were used. The standard deviation is consistently higher than the mean. This is driven by the fact that a considerable number of firms have barely used TAW while others used them intensively. The 95 percentile ranges from 8.2 to 44.1 percent for the subset of observations that used TAW. These descriptive findings highlights once more that temporary agency work has become a non-negligible input factor.

Figure 2: Ratio of temporary agency workers to core workforce per size-class, full dataset



Source: *cost structure survey*; own calculations.

This also applies to all size classes. As Figure 2 reveals, the ratio of TAW to regular employees increased across all size classes between 2003 and 2011. In addition, the graphic shows that the intensity of TAW usage increases with firm size. While the average ratio for firms with 20-49 employees in the entire dataset was 2.9 percent in 2011, it was 4.7 percent in the size class of 50 to 99 employees and 6.3 percent in the class of firms with 250 or more employees. Hence, larger firms use not only "more" TAW because they are bigger, they also use relatively more TAW than smaller firms. This finding is in line with the literature that points to the fact that employment protection legislation increases

In order to rule out that the high shares are biased as a result of the data cleaning process, we reproduced the descriptive analysis (Figure 1) with all 143,694 observations before any data cleaning. Missing observations for *cost for temporary agency worker* are treated as if the company has not used TAW. As Figure 1 in the appendix shows, the frequency of use and the shares shown here are not distorted by the data cleaning process.

16 See Table D-6 in the appendix.

with increasing company size, which in turn makes the use of TAW more attractive (Hirsch & Müller, 2012).

Summing up, descriptive analyses provide further evidence that temporary agency work is a non-negligible input. As such, it supports the hypothesis that neglecting TAW might cause biased productivity estimates.

5. Results

The econometric analysis starts with analyzing the differences in labor productivity. We consider labor productivity separately in a first step for two reasons: First, it is a widely used measure, whether in politics, in collective bargaining, or in scientific research.[17] Incorrect estimates could, for example, lead to excessive wage demands, support the increase of regulatory burdens, or support the increase of tax burdens for other purposes (e.g. additional taxes on energy to foster green economy) because the industries are considered productive enough to bear additional burdens. Secondly, labor productivity is a measure of the intensity with which the labor input is used. If there are any distortionary effects from neglecting temporary agency work, they should become evident through this productivity measure.

The second part of the analysis tests whether TFP and the input coefficients are biased if temporary agency work is neglected. To this end, the above-described structural approach is used. The production function is estimated with and without TAW, and it is also tested whether the resulting TFPs and the input coefficients significantly differ.

Labor Productivity

Labor productivity is calculated using deflated value added. Deflation is carried out using the Producer Price Index (PPI) at the four-digit industry level. The analysis is conducted at aggregated level and at the two-digit industry level. Analyses at a lower level, e.g. the three-digit industry level, are not possible due to the privacy policies of the German statistical offices. Labor productivity is calculated with and without TAW at the firm level. The *t*-test for two samples with unequal variance is applied in order to test whether there is a significant difference in the productivity of the German manufacturing industry or in its subsectors. As the focus at this point is on the effect of TAW on average productivity of sectors, the full dataset is used instead of a subsample of firms that made use of TAW in the respective years.

As argued in section 4, the initial assumption is that the TAW are as costly as regular employees with equal qualification. The number of TAW per firm is then calculated as $L_{T,it} = s_{c,it} L_{P,it}$ with $s_{c,it}$ defined as $C_{T,it}/C_{P,it}$. The full labor input is the sum of permanent and temporary workers $\left(L_{it} = L_{T,it} + L_{P,it}\right)$ and is used as denominator (Y_{it}/L_{it}). As also discussed in section 4, the assumption regarding the relationship between the cost of a temporary workers and the cost for a regular employee of a firm affects the number of TAW and, thus, the differences in labor productivity. To derive robust results and to test whether smaller or larger numbers of TAW would make a difference, we also use a discount

[17] The EU Commission evaluates the competitiveness of each country using, *inter alia*, the indicators “labour productivity per hour worked,” “labour productivity per person employed,” and “labour productivity per person employed in manufacturing” (European Commission, Directorate-General for Enterprise and Industry, 2013).

factor d, ranging from 0.5 to 1.5, and derive the number of TAW per firm by $L_{T,it} = L_{P,it}s_{c,it}/d$.[18] The way we utilize this discount factor, it needs to be interpreted as an adjustment factor in the cost relationship:[19] A value of 0.5 means that a TAW is actually only half as expensive as regular employee for the renting firm. In contrast, a factor of 1.5 means that the cost for a TAW is 50 percent higher compared to that for a permanent employee. In this case, the approximated number of TAW should be 33 percent lower.

Table 1 shows the average difference in labor productivity. Hence, it compares labor productivity when calculated with and without TAW, measuring the percentage deviation $\left((Y_{it}/L_{it})/\left(Y_{it}/L_{P,it}\right) - 1\right)$. The negative sign shows how much smaller the average labor productivity becomes once TAW are taken into account. In other words, it shows by how much labor productivity is otherwise overestimated. The third column shows the average difference for the starting assumption of equal cost for both types of employees ($d = 1$). Under this assumption, the average labor productivity of the German manufacturing industry would be 3.3 percent smaller. This difference is significant at the 1 percent level. If we consider the case that the relative costs for TAW are not equal to one but that TAW are actually only half as expensive ($d = 0.5$), the average bias increases to -5.9 percent. Even in the case that TAW are 1.5 times more expensive than regular employees ($d = 1.5$), which in turn would reduce the number of TAW given the observed spending for TAW $\left(C_{T,it}\right)$, the bias would still be -2.3 percent and significant at the 1 percent level.

This results show that regardless of the “correct,” but unknown, ratio between costs for TAW and the costs for permanently employed workers, actual labor productivity of the German manufacturing industry is significantly lower once TAW are accounted for. Or, conversely, the traditionally calculated labor productivity, that is without TAW because they are not in the statistics, leads to an overestimation of the labor productivity for the German manufacturing industry.

This, however, does not apply for all 2-digit sectors, as shown by further results in Table 1. When assuming $d = 1$, we see that labor productivity in 7 of 22 sectors does not significantly differ. This reveals that the results for the entire manufacturing industry are driven by selected 2-digit sectors. However, for one of these sectors, *Manuf. of leather and related products (15),* the insignificance might be caused by the small number of observations. In addition, in three of the seven sectors the picture is mixed (ISIC: 13, 17, 32). While the differences in productivity are not significant in the case of $d = 1$, they become significant in the case of $d = 0.5$.[20] It likewise reveals the assumption about the cost relationship and the chosen level for d influences the test results in these selected industries.

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[18] For a detailed discussion on how to derive the number of TAW from cost data and on the discount factor *d*, we refer to section B of the appendix.

[19] Alternatively *d* could be interpreted as differences in productivity between the two types of workers. Let us use d_p to distinguishing this case. When using this productivity difference approach, a 0.5 would mean that TAW are only half as productive as regular employees while 1.5 would mean that they are 50 percent more productive. However, when using this interpretation, $L_{it,T}$ needs to be calculated as $L_{it,P}s_{it}d_p$. Hence, the number of “productive heads” would be lower in case of $d_p = 0.5$. In essence, however, this deviating interpretation of d would only change the way the results need to interpreted – not the results themselves. For example, the equivalent of $d_p = 0.5$ is a discount factor of $d = 2$. In both cases the $L_{T,it}$, that is the heads or the productive heads, would be only half as high in the case of $d_p = d = 1$.

[20] Figure 2 in the appendix shows at which level of d the differences in labor productivity become significant for these three industries.

However, the results of Table 1 also show that the assumption regarding d affects the magnitude of the differences in labor productivity, but not, generally, the statistical significance in the remaining industries. Hence, using $d = 1$ in the latter process will most likely deliver robust results.

Table 1: Average percentage difference in labor productivity if TAW is included, entire dataset

	Ind. code	d=1	d=0.5	d=1.5	N
Manufacturing	10t33	-3.3%***	-5.9%***	-2.3%***	125,526
Manuf. of food prod.	10	-3.6%**	-6.3%***	-2.5%	14,263
Manuf. of beverages	11	-3.8%	-6.7%	-2.7%	2,249
Manuf. of textiles	13	-1.9%	-3.4%***	-1.3%	3,512
Manuf. of wearing apparel	14	-0.5%	-0.9%	-0.3%	1,985
Manuf. of leather & related prod.	15	-1.7%	-3.1%	-1.2%	930
Manuf. of wood & prod. of wood etc.	16	-3.0%**	-5.4%***	-2.1%*	3,274
Manuf. of paper & paper prod.	17	-2.0%	-3.7%***	-1.4%	3,415
Printing & reprod. of recorded media	18	-2.1%*	-3.7%***	-1.4%	2,914
Manuf. of chemicals & chemical prod.	20	-2.3%**	-4.3%***	-1.6%	6,492
Manuf. of basic pharm. prod. & pharm. prep.	21	-2.2%	-4.0%	-1.5%	1,588
Manuf. of rubber & plastics prod.	22	-3.6%***	-6.5%***	-2.5%***	7,540
Manuf. of other non-metallic mineral prod.	23	-2.9%***	-5.2%***	-2%**	6,469
Manuf. of basic metals	24	-3.4%***	-6.1%***	-2.3%*	4,929
Manuf. of fabricated metal prod., exc. mach. & equip.	25	-3.8%***	-6.7%***	-2.6%***	15,399
Manuf. of computer, electronic & optical prod.	26	-2.7%**	-4.9%***	-1.9%	6,218
Manuf. of electrical equipment	27	-3.6%***	-6.4%***	-2.5%***	7,453
Manuf. of machinery & equipment	28	-3.5%***	-6.2%***	-2.4%***	19,701
Manuf. of motor vehicles, trailers & semi-trailers	29	-5.2%***	-9.1%***	-3.7%**	5,285
Manuf. of other transport equipment	30	-6.2%***	-10.7%***	-4.3%**	1,492
Manuf. of furniture	31	-3.0%***	-5.4%***	-2.1%*	3,012
Other Manuf.	32	-1.8%	-3.3%**	-1.2%	4,428
Repair & installation of machinery & equipment	33	-7.2%***	-12.1%***	-5.1%***	2,978

Source: *cost structure survey*; own calculations; *** p<0.01, ** p<0.05, * p<0.1.

Summing up, we can partly confirm the hypothesis that labor productivity estimates are biased when ignoring TAW as inputs. In other words, the labor productivity of the German manufacturing industry is overestimated as long as it is calculated based on official number of persons employed in the manufacturing firms. This is due to the significant number of TAW that actually work in manufacturing firms but that are not assigned to the workforce of manufacturing firms for statistical purposes. This holds for the German manufacturing industry as a whole, as well as for 15 subsectors. Among them are important sectors, including *mechanical engineering*, *automotive*, as well as *manufacturing of electrical equipment, electronic, and optical products*. Thus, labor productivity is particularly overestimated in industries that are export intensive and regarded as highly competitive.

Total Factor Productivity

This section tests whether TFP estimates are biased when TAW is ignored in the estimations. It is also tested whether the input coefficients are significantly different once temporary agency work is taken into account. Here the effect on the labor coefficient is interesting since TAW can be seen as additional labor input. A prediction for the direction of the bias of the labor coefficient is not straightforward, as shown in section 2. However, if the effect of TAW on output is found to be positive and significant, it is most likely that the labor coefficient captures part of this effect in all estimations without TAW. Hence, we expect the coefficients of labor in estimations without TAW to be upward biased if the coefficient of TAW is positive and *vice versa*.

An initial impression of whether or not TAW are a relevant input factor in the production function estimation is provided by OLS. The estimation is conducted for the entire manufacturing industry as well as for each of the 22 two-digit subsectors. The regression results provide a mixed picture. The coefficient for TAW is positive and significant for the manufacturing industry as a whole. The coefficients are positive and significant for 8 out of 22 sectors, but negative and significant for two sectors.[21] The magnitude of the significant coefficients is between -0.03 and 0.12. These first results suggest that ignoring TAW might not necessarily lead to biased labor coefficients or biased TFP estimates in all industries.

Table 2 shows the estimations conducted by means of the structural approach described in section 4. Columns three to six provide the estimation results when TAW are included. Starting with the aggregated manufacturing industry, we find the coefficient for TAW is significant at the 1 percent level. However, at about 0.01, the effect of TAW on value added is small.

A look at the individual sectors shows a mixed picture: TAW are found to have a significant effect on value-added in fourteen of the twenty-two German manufacturing industries. However, with elasticities between 0.01 and 0.04 the overall effect on value added is modest in comparison to the labor coefficient. Temporary agency work has no significant effect on value-added in seven industries. Comparing the findings of Table 2 with those in Table 1 reveals that there is a strong overlap between industries that are characterized by significant differences in labor productivity and those that have significant coefficients for TAW. This suggests that the results of the production function approach are not driven by subsampling, the significantly lower number of observations, or the like.[22] Rather it seems robust to conclude that TAW significantly impact output in these fourteen sectors during the observation period.

The estimated coefficients for permanent labor and capital are reasonable and generally lower than, but in the neighborhood of, the OLS coefficients.[23] This is in line with the expectation that structural approaches reduce the magnitude of coefficients. (Doraszelski & Jaumandreu, 2013). The Hansen-tests performs well in sixteen industries and, if we include those sectors in which the Hansen-test is not rejected at the 1 percent level, even in 20 of the 22 sectors. However, the null hypothesis must be rejected in the remaining two estimations.[24]

Thus we conclude that there is evidence that TAW provides a small but significant contribution to the production process for fourteen industries. Hence, one of the preconditions for the hypothesis is partly confirmed: temporary agency work has a significant effect on firm performance. This allows for testing

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[21] We refrain from presenting the regression results for space reasons. However, Table D-7 in the appendix provides detailed results for each OLS regression.

[22] The number of observations drops to 35,909 for two reasons: First, we use twice lagged temporary labor variables. Hence, we need a minimal number of three successive observations for a firm to be included in the estimation. Second, we can use only observation with $TAW \neq 0$ since the logarithm of zero is undefined.

[23] The only exception is the pharma sector (ISIC 21) with a labor coefficient larger than one und an insignificant capital coefficient. Although this is in line with the OLS estimate for this sector, we do not consider this result convincing. However, since the coefficient for TAW is insignificant in the estimations and TAW usage also has no significant effect on labor productivity (see Table 2), the sector is not relevant in further discussion and the insufficient estimation can be ignored.

[24] A large set of instruments has been used to enhance the Hansen-test statistics in these cases. *Inter alia,* year dummies for period 2007 to 2011 are used in order to capture the effects of the crisis period 2007 to 2009 and the recovery in 2010 and 2011, or, $l_{P,it-1}$ and $l_{P,it-2}$ are used instead of $l_{P,it}$ and $l_{P,it-1}$. While using year dummies enhanced the coefficients for TAW in some cases, the Hansen-test statistics did not improve to a degree that the null hypothesis cannot be rejected.

the hypothesis of whether ignoring TAW significantly biases the estimated TFP as well as the coefficients within production function estimations.

Table 2: Results of the structural estimation of the production function[25]

		estimation incl. TAW				estimation without TAW			Diff. between	
Ind. Code	N	T	L	K	Hansen-Test (Chi2)	L	K	Hansen-Test (Chi2)	L	K
10t33[a]	35,909	0.008***	0.850***	0.105***	149.58***	0.863***	0.107***	141.98***	0.013**	0.003
10[d]	3,323	-0.013	0.671***	0.228***	8.06**	0.664***	0.224***	6.69**	-0.007	-0.004
11[a]	592	0.052	0.681***	0.197***	2.98	0.741***	0.195***	1.88	0.060	-0.002
13[d]	698	0.023***	0.789***	0.187***	1.91	0.820***	0.186***	3.01	0.031	-0.001
14[a]	153	0.008	0.668***	0.330***	4.72	0.682***	0.310***	3.61	0.014	-0.019
15[b]	167	-0.027	0.807***	0.133***	1.44	0.718***	0.122***	4.11	-0.090	-0.012
16[b]	822	0.04***	0.735***	0.074***	9.61	0.798***	0.074***	8.18	0.063	0.000
17[a]	1,080	0.025***	0.717***	0.205***	5.76	0.749***	0.203***	4.61	0.032	-0.002
18[a]	482	-0.014	0.884***	0.097***	4.56	0.843***	0.109***	0.72	-0.041	0.011
20[a]	2,321	0.031***	0.715***	0.182***	7.52	0.745***	0.171***	7.84**	0.030	-0.011
21[e]	496	0.018	1.023***	0.050	7.29	0.981***	0.056	6.54	-0.042	0.006
22[a]	2,424	0.013**	0.788***	0.117***	10.08**	0.809***	0.124***	8.49**	0.021	0.007
23[a]	1,981	0.022***	0.780***	0.162***	2.55	0.811***	0.161***	0.45	0.030	-0.001
24[c]	1,787	0.018***	0.881***	0.136***	12.51**	0.953***	0.123***	2.67	0.073	-0.013
25[a]	4,376	0.009***	0.833***	0.087***	18.86***	0.852***	0.091***	13.41***	0.019	0.004
26[d]	1,639	0.002	0.808***	0.199***	7.11*	0.808***	0.191***	7.93**	-0.030	0.004
27[a]	2,331	0.026***	0.817***	0.118***	3.90	0.896***	0.124***	2.21	0.079**	0.006
28[a]	6,194	0.029***	0.938***	0.077***	41.95***	0.976***	0.075***	27.63***	0.039**	-0.002
29[a]	1,937	0.021***	0.710***	0.093***	6.20	0.747***	0.096***	6.44*	0.037	0.002
30[a]	607	0.009	0.885***	0.134***	4.14	0.886***	0.133***	4.97	0.000	-0.001
31[a]	756	0.016**	0.851***	0.111***	1.09	0.870***	0.109***	0.02	0.019	-0.002
32[a]	771	0.012*	0.810***	0.149***	6.93	0.817***	0.154***	7.38*	0.007	0.006
33[a]	972	0.033*	0.978***	0.06***	1.68	1.012***	0.067***	3.26	0.034	0.008

Source: *cost structure survey*; own calculations;

*** p<0.01, ** p<0.05, * p<0.1; N applies to estimations with and without TAW;

a: basic specification, second stage estimation using following instruments: $l_{T,it-1}, l_{T,it-2}, l_{P,it}, l_{P,it-1}, k_{it}, k_{it-1}$;

b: second stage estimation using following instruments: $l_{T,it-1}, l_{T,it-2}, l_{P,it}, l_{P,it-1}, l_{P,it-2}, k_{it}, k_{it-1}, k_{it-2}$;

c: second stage estimation using following instruments: $l_{T,it-1}, l_{T,it-2}, l_{P,it-1}, l_{P,it-2}, k_{it}, k_{it-1}$;

d: second stage estimation using following instruments: $l_{T,it-1}, l_{T,it-2}, l_{P,it-1}, l_{P,it-2}, k_{it}$;

e: second stage estimation using following instruments: $l_{T,it-1}, l_{T,it-2}, l_{P,it}, l_{P,it-1}, k_{it}, k_{it-1}$, time dummies.

To this end, we first compare the coefficients of the estimations with and without TAW.[26] We expect to find significant difference between the coefficients for permanent labor for those industries in which

[25] The standard errors of the coefficients and the degrees of freedom for the Hansen-test are omitted for space considerations. All details for the basic specification are provided in in Table D-8 of the appendix. We only deviate from the basic specification if the Hansen-test performs better with different instruments while the coefficients stay about the same. The only exception to that rule is sector ISIC 10, where the Hansen-test performs better and the coefficients are closer to the OLS estimate.

TAW proved to have a significant effect. Columns seven to nine in Table 2 contain the labor and capital coefficients for the estimations without TAW. Columns ten and eleven contain the differences between the coefficients. The significance between the coefficients is tested using the Welch's *t*-test.

The results of the tests on differences between the labor coefficients only partly confirm the initial expectation. Column ten reveals that the sign of the differences between the coefficients mostly correspond to the sign of the TAW coefficient. In industries with significant coefficients for TAW, the magnitude of the difference between the labor coefficients is close to, or often even larger than, the corresponding coefficient for TAW. This finding indicates that the labor coefficient partially captures the effect of TAW if TAW is neglected in the estimation. That the labor coefficients are somewhat larger indicates an overshooting and an upward bias of the labor coefficients when TAW are ignored. However, the labor coefficients are mostly not significantly different between estimations with or without TAW, except for two industries and the manufacturing industry as a whole. The labor coefficients are significantly different at the 5 percent level in these three estimations. However, because the null-hypothesis of the Hansen-test is rejected for these three estimations, the statistical significance of the differences between the labor coefficient is not certain. Finally, as expected, there is little difference between the capital coefficients. Summing up, due to the missing or only weakly statistically significance of the differences between the labor coefficients in most sectors, we cannot confirm the hypothesis of potential biases of the input coefficients.

Table 3: Average TFP in estimations with and without TAW

Ind. Code	N	Mean TFP (not contr. for T)	Mean TFP (contr. for T)	Diff.	Std.Err. of Diff.	t-value	p-value	df_t
10t33	35,909	9.873	9.975	-0.102	0.001	-70.55	0.00	71,761.5
13	698	8.839	8.953	-0.114	0.007	-15.74	0.00	1,393.9
16	822	10.646	10.895	-0.249	0.014	-17.16	0.00	1,637.7
17	1,080	8.806	8.903	-0.098	0.006	-15.09	0.00	2,150.0
20	2,321	9.577	9.508	0.068	0.007	10.42	0.00	4,632.2
22	2,424	9.758	9.968	-0.210	0.006	-37.64	0.00	4,788.4
23	1,981	9.240	9.346	-0.106	0.007	-16.04	0.00	3,956.2
24	1,787	9.213	9.335	-0.122	0.007	-17.22	0.00	3,566.4
25	4,376	10.157	10.302	-0.145	0.005	-31.61	0.00	8,703.5
27	2,331	9.452	9.935	-0.482	0.005	-106.69	0.00	4,404.8
28	6,194	9.959	10.085	-0.126	0.003	-42.82	0.00	12,378.6
29	1,937	10.649	10.846	-0.197	0.011	-18.49	0.00	3,861.0
31	756	9.779	9.818	-0.039	0.007	-5.46	0.00	1,508.8
32	771	9.460	9.572	-0.112	0.011	-10.19	0.00	1,539.2
33	972	9.864	10.078	-0.214	0.008	-28.21	0.00	1,938.0

Source: *cost structure survey*; own calculations.

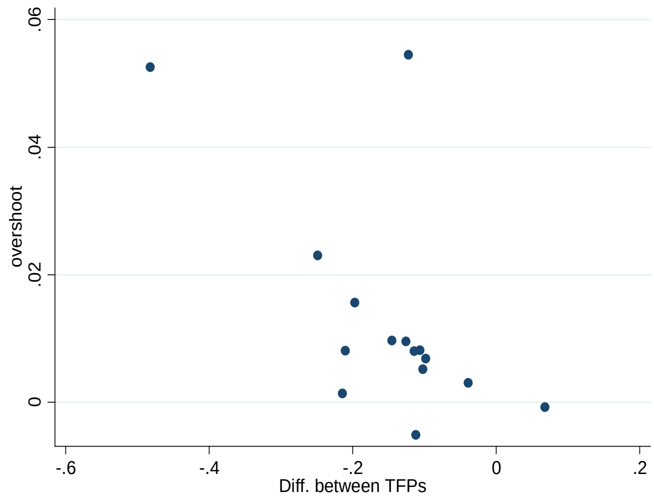
This leaves the question of whether TFP, like labor productivity, significantly differs. The comparison is conducted for industries in which the coefficient of TAW was significant. TFPs are compared using

[26] The estimations without TAW uses the same samples, applies the same control function approach, and utilizes the same instruments as the estimations with TAW.

Welch's *t*-test, which allows for unequal variance between two samples. Column three in Table 3 provides average TFPs based on estimations without TAW, column four contains average TFPs based on estimations including TAW, while column five and following depict the differences and whether the means are significantly different.

Table 3 shows that the TFPs differ on average. These differences are all statistically significant at the one percent level. A correlation analysis and a visual comparison by means of a scatter plot also shows that the magnitude of the differences and the magnitude of the TAW coefficient are negatively correlated: the larger the coefficient for TAW, the larger is the difference between the TFPs.[27] In other words, on average TFP is underestimated if TAW is ignored. Therefore the results confirm the initial hypothesis that productivity estimates of German manufacturing firms and industries are biased due to the underestimation of labor input.

Figure 3: Relationship between differences in TFP and the overshooting of labor coefficients, two-digit industries



Source: *cost structure survey*; own calculations

However, the direction of the bias is somewhat surprising. Given the mostly positive coefficients for TAW, one intuitively expects that TFPs are upward biased when TAW are ignored. How can this be explained, also in light of the results regarding the differences in labor productivity? The fact that the differences between the labor coefficients are generally larger than the coefficients for TAW in combination with Eq. (1) to Eq. (3) provides an indication for the answer: Mathematically, TFP serves as a residual or a multiplier that explains the difference between the product of the inputs, which are normalized by the coefficients, and the observed output. Here the differences between the labor coefficients and the magnitude of the TAW coefficients come into play. As pointed out, the magnitude of the differences between the labor coefficients is generally larger than the coefficient of TAW. This overshooting has the consequence that the multiplier, that is the TFP, becomes smaller. [28] Figure 3 supports this reasoning, showing that there is a strong relationship between the size of overshooting and

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[27] See Figure 3 in the appendix.

[28] This overshooting is calculated as difference between the differences of labor coefficients and the coefficient of TAW.

the differences in TFP. In other words: although the differences in the labor coefficients are not large enough to be considered as significantly different in most sectors, they are large enough to lead to significantly different TFP estimates.

Robustness Checks

Performing the analysis not only for the aggregated manufacturing industry but also for all two-digit subsectors serves as a first robustness check. The results for the two-digit subsectors confirm the general finding that productivity estimates are incorrect if TAW, as part of the labor input, is ignored. However, the results also show that not all sectors are affected to the same extent, rather that there is a subset of sectors driving the results.

We conduct further estimations in order to check whether the results are also robust for sub-periods or whether the assumed cost relationship (d) affects TFP estimates. In a first step we test the robustness of the results for labor productivity by splitting the sample into the 2003 to 2007 period and the 2008 to 2011 period. Given that TAW usage grew from 330,000 in 2003 to 715,000 in 2007, while the number of TAW was between 760,000 and 880,000 after 2008, we expect to find relatively more sectors with significant differences in labor productivity in the second period. Moreover, since the number of TAW is growing over time, we can expect the differences in labor productivity to be larger in the second sub-period compared to the first sub-period and, consequently, also larger than for the entire period.

Table 4: Average percentage difference in labor productivity if TAW is included, two sub-periods

Ind. code	2003 - 2007 period				2008 - 2011 period			
	d=1	d=0.5	d=1.5	N	d=1	d=0.5	d=1.5	N
10t33	-2.9%***	-5.1%***	-2.0%***	65,047	-3.9%***	-6.9%***	-2.7%***	60,479
10	-3.1%	-5.4%**	-2.1%	7,129	-4.1%**	-7.2%***	-2.9%	7,134
11	-3.1%	-5.6%	-2.2%	1,298	-4.9%	-8.5%	-3.4%	951
13	-1.6%	-2.9%	-1.1%	2,005	-2.3%	-4.1%**	-1.6%	1,507
14	-0.4%	-0.7%	-0.3%	1,241	-0.6%	-1.2%	-0.4%	744
15	-1.3%	-2.4%	-0.9%	564	-2.2%	-3.9%	-1.5%	366
16	-2.5%	-4.6%***	-1.8%	1,698	-3.6%*	-6.3%***	-2.5%	1,576
17	-1.6%	-3.0%	-1.1%	1,749	-2.4%	-4.4%**	-1.7%	1,666
18	-1.7%	-3.1%	-1.2%	1,610	-2.5%	-4.4%***	-1.8%	1,304
20	-1.9%	-3.6%**	-1.3%	3,314	-2.8%	-5.1%***	-1.9%	3,178
21	-1.7%	-3.2%	-1.2%	867	-2.6%	-4.7%	-1.8%	721
22	-2.9%***	-5.3%***	-2.0%**	3,843	-4.3%***	-7.7%***	-3%***	3,697
23	-2.4%*	-4.3%***	-1.7%	3,488	-3.5%**	-6.3%***	-2.5%*	2,981
24	-2.9%*	-5.2%***	-2.0%	2,541	-4.0%**	-7.2%***	-2.8%*	2,388
25	-3.2%***	-5.7%***	-2.2%***	7,193	-4.4%***	-7.7%***	-3.1%***	8,206
26	-2.3%	-4.1%**	-1.6%	3,208	-3.1%*	-5.6%***	-2.2%	3,010
27	-3.3%***	-5.9%***	-2.3%**	3,943	-3.9%***	-7.0%***	-2.7%**	3,510
28	-3.1%***	-5.6%***	-2.2%***	10,633	-3.9%***	-6.9%***	-2.7%***	9,068
29	-4.5%***	-8.0%***	-3.1%**	2,964	-6.1%*	-10.5%***	-4.3%	2,321
30	-5.2%**	-9.1%***	-3.6%	836	-7.4%**	-12.6%***	-5.2%*	656
31	-2.6%*	-4.7%***	-1.8%	1,666	-3.6%**	-6.4%***	-2.5%	1,346
32	-1.3%	-2.4%	-0.9%	2,153	-2.3%	-4.2%**	-1.6%	2,275
33	-8.1%***	-13.6%***	-5.8%***	1,104	-6.7%***	-11.2%***	-4.7%***	1,874

Source: *cost structure survey*; own calculations; *** p<0.01, ** p<0.05, * p<0.1.

The results in Table 4 confirm these expectations. First, the differences in labor productivity are higher in the 2008 to 2011 period compared to the 2003 to 2007 period. Second, the average differences in labor productivity for the entire period (Table 1) are between the average differences in the two sub-periods. Third, there are two more sectors with significant differences in the 2008-2011 period than in the earlier period. However, it is worth noting that in 13 out of 15 sectors, we find significant differences in labor productivity over not just the entire time spam, but also the two sub-periods. Therefore, it can be concluded that (i) the results in Table 1 are robust; and (ii) that the differences in labor productivity are driven by the same the two-digit sectors over the entire period.

Table 5: Production function estimations with $d = 0.5$ and $d = 1.5$.[29]

Ind. Code	N	estimations with d=0.5 T	L	K	Hansen (Chi2)	estimations with d=1.5 T	L	K	Hansen (Chi2)
10t33[a]	35909	0.004***	0.850***	0.105***	149.58***	0.012***	0.850***	0.105***	149.58***
10[d]	3323	-0.006	0.671***	0.228***	8.06**	-0.019	0.671***	0.228***	8.06**
11[a]	592	0.026	0.681***	0.197***	2.98	0.078	0.681***	0.197***	2.98
13[d]	698	0.011***	0.789***	0.187***	1.91	0.034***	0.789***	0.187***	1.91
14[a]	153	0.004	0.667***	0.33***	4.7	0.012	0.667***	0.330***	4.7
15[b]	167	-0.013	0.807***	0.133***	1.44	-0.04	0.807***	0.133***	1.44
16[b]	822	0.02***	0.735***	0.074***	9.61	0.06***	0.735***	0.074***	9.61
17[a]	1080	0.013***	0.717***	0.205***	5.76	0.038***	0.717***	0.205***	5.76
18[a]	482	-0.007	0.884***	0.097***	4.56	-0.022	0.884***	0.097***	4.56
20[a]	2321	0.015***	0.715***	0.182***	7.52	0.046***	0.715***	0.182***	7.52
21[e]	496	0.009	1.023***	0.050	7.28	0.027	1.023***	0.050	7.28
22[a]	2424	0.006**	0.788***	0.117***	10.08**	0.019**	0.788***	0.117***	10.08**
23[a]	1981	0.011***	0.780***	0.162***	2.55	0.033***	0.780***	0.162***	2.55
24[c]	1787	0.009***	0.88***	0.136***	12.52**	0.028***	0.881***	0.136***	12.52**
25[a]	4376	0.005***	0.833***	0.087***	18.86***	0.014***	0.833***	0.087***	18.86***
26[d]	1639	0.001	0.808***	0.199***	7.11*	0.003	0.808***	0.199***	7.11*
27[a]	2331	0.013***	0.817***	0.118***	3.9	0.04***	0.817***	0.118***	3.9
28[a]	6194	0.015***	0.938***	0.077***	41.95***	0.044***	0.938***	0.077***	41.95***
29[a]	1937	0.011***	0.710***	0.093***	6.19	0.032***	0.710***	0.093***	6.19
30[a]	607	0.004	0.885***	0.134***	4.14	0.013	0.885***	0.134***	4.14
31[a]	756	0.008**	0.851***	0.111***	1.09	0.024**	0.851***	0.111***	1.09
32[a]	771	0.006*	0.810***	0.149***	6.93	0.018*	0.810***	0.149***	6.93
33[a]	972	0.016*	0.978***	0.059***	1.68	0.049*	0.978***	0.060***	1.68

Source: *cost structure survey*; own calculations;

*** p<0.01, ** p<0.05, * p<0.1; N applies to estimations with and without TAW;

a: basic specification, second stage estimation using following instruments: $l_{T,it-1}, l_{T,it-2}, l_{P,it}, l_{P,it-1}, k_{it}, k_{it-1}$;

b: second stage estimation using following instruments: $l_{T,it-1}, l_{T,it-2}, l_{P,it}, l_{P,it-1}, l_{P,it-2}, k_{it}, k_{it-1}, k_{it-2}$;

c: second stage estimation using following instruments: $l_{T,it-1}, l_{T,it-2}, l_{P,it-1}, l_{P,it-2}, k_{it}, k_{it-1}$;

d: second stage estimation using following instruments: $l_{T,it-1}, l_{T,it-2}, l_{P,it-1}, l_{P,it-2}, k_{it}$;

e: second stage estimation using following instruments: $l_{T,it-1}, l_{T,it-2}, l_{P,it}, l_{P,it-1}, k_{it}, k_{it-1}$, time dummies.

In order to test whether the results of the production function estimations are driven by the assumption of equal costs for both types of workers ($d = 1$), the estimations are also conducted for the assumption of $d = 0.5$ and $d = 1.5$. The results in Table 5 show that such change in the assumption about the cost relationship only affects the magnitude of the coefficients for TAW, but not the significance. It also does not significantly change the coefficients of permanent labor or capital, nor does it change the statistical significance of these coefficients. The magnitude of the changes in the coefficients for TAW matches exactly with the value of the discount factor. This is in line with what one should expect, because d just imposes a linear transformation of the number of TAW. Using a d of 0.5 doubles the number of TAW. Accordingly, the coefficients for TAW in each sector are only half as high compared to the estimations under the assumption of $d = 1$. In contrast, the coefficients for TAW are 1.5 times

[29] The standard errors of the coefficients and the degrees of freedom for the Hansen-test are omitted for space considerations. All details for the basic specification are provided in Table D-9 in the appendix.

larger if $d = 1.5$ is assumed. Given that the coefficients for permanent labor and capital do not change and that the coefficient for TAW captures the changes in d, the calculated TFP also does not differ between estimations based on the assumption of $d = 0.5$ or $d = 1.5$ and estimations under the assumption of equal cost for both types of employees $(d = 1)$.[30]

Summing up, the difference in labor productivity increases over time as a result of the growth in the number of TAW. Apart from that, the finding that labor productivity is biased in several subsectors and the manufacturing industry is robust. In addition, the assumption about the cost relationship is not crucial for the results of the production function estimation. Regardless of which d is the "correct" one, TFP estimates estimates in many industries are biased due to the omission of part of the labor input, namely the omission of temporary agency work.

6. Conclusion

Labor input is an essential variable in the calculation of the most common productivity measures, e.g. labor productivity and total factor productivity. But the nature of labor relations has changed noticeably since the mid-1990s. Atypical forms of employment are now an important form of employment in all European nations. Temporary agency work, as a type of atypical employment, is also growing dynamically. The effect of temporary agency workers (TAW) usage on firm performance is, however, rarely studied. A second issue is becoming increasingly important as more and more companies use this type of labor: do productivity estimates appropriately account for the increasing use of TAW in firms?

The study reveals for the case of Germany that statistics about labor usage in firms do not necessarily include TAW. It shows theoretically that such misspecification of a production function can lead to biased estimates for firm productivity and might also lead to biased estimates for the elasticities of labor and capital.

At the empirical level, the study analyzes total factor productivity, estimated using a structural approach, and labor productivity, calculated as real value added over total labor input. We find that labor productivity of the German manufacturing industry is, on average, upward biased by 3.3 percent if temporary agency work is omitted. However, evidence is mixed for subsectors: while the differences are significant in 15 of the 22 subsectors, they are not significantly different in the remaining seven subsectors. For the industries with statistically significant results, labor productivity is overestimated on average by 2 to 7 percent.

The estimation of total factor productivity has three main findings. Firstly, temporary agency work is significantly positive related to firm performance for the entire manufacturing sector and 14 subsectors. Hence, the study provides evidence that the use of TAW is beneficial for firms in these sectors. Secondly, estimated total factor productivity differs significantly in all industries with significant coefficients for temporary agency work. The average difference in TFP is about 1.6 percent. Finally, although the coefficients for the regular labor variable differ in estimations with and without temporary agency work, the differences are not statistically significant in all but two sectors. This means that the estimations of production function without TAW as input can still provide unbiased elasticities for regular labor and capital even though TFP is biased.

[30] TFP result tables for estimations under the assumption of $d = 0.5$ and $d = 1.5$ are provided in Table D-10 in the appendix.

These results rely on the assumption that TAW are as costly as regular employees for the firms. When dropping that assumption and assuming lower costs for TAW, the differences in labor productivity are even more pronounced and the number of sectors with significant differences in labor productivity increases. Accordingly, the coefficients for TAW change with changing cost assumptions. However, the changing cost assumption does not affect the TFP estimates or the coefficients for permanent labor and capital. This holds true for the magnitude of the coefficients and the TFPs as well as for the statistical significance. Hence, assuming higher or lower costs for TAW in comparison to permanent labor does not affect the main results of the production function estimations. It is therefore safe to conclude that productivity figures for German manufacturing industries are inaccurate without the inclusion of temporary agency work.

The results of the study are of importance beyond the specific case of the German manufacturing industry. Generally, productivity is used as a central indicator when analyzing the competitiveness of firms, sectors or nations, as for example in the annual *Member States' Competitiveness Report* released by the European Commission. It also plays a vital role in the context of collective bargaining processes, since wage claims are, *inter alia,* justified with productivity improvements. As this study reveals, these productivity indicators can be biased if the increasing importance of atypical forms of employment is disregarded. As a consequence, economic policy recommendations and the European debate about competitiveness of nations and industries can be based on incorrect data about productivity. Furthermore, collective bargaining parties might possibly negotiate on the basis of incorrect assumptions about recent productivity gains. However, it is an open question whether the omission of TAW is an issue in other European nations. Therefore, further research is needed to reveal the differences in national statistics and national firm surveys in order to allow undistorted productivity estimates and productivity comparisons between European industries.

Appendix

A Literature review

This overview presents related studies focusing on the relationship of TAW use with firm productivity, sales growth, and other indicators of firm performance. In comparison to the main text, this provides additional information on each study, also showing how the present study differs. The main aspects are summarized in Table A-1.

Using data on 1,382 Swiss firms from all sectors over the 1998 to 2000 period, Arvanitis (2005) analyzes the effect of various forms of labor contracts on firm performance, among them temporary agency work, which is modeled using a dummy variable. Firm performance is measured by the log of sales per capita and two dummies. One captures product innovation while the other takes the value of one if the firm introduced some process innovation. The analysis of the cross section data by means of OLS indicate that temporary agency work does not significantly affect firm performance. The results of the probit regressions for innovation performance show that temporary agency work has a positive effect on product innovation but no significant effect for process innovation. A second study with a similar outcome is Kleinknecht et al. (2006), which uses a dataset of 590 Dutch firms across several sectors over the 1992 to 1994 period. The dependent variables are sales growth and employment growth, while the percentage of hours worked by TAW on total hours worked is used as a control variable. Using OLS, the analysis cannot confirm a significant relationship between the hours worked by TAW and sales growth or employment growth. A weakly significant, but negative, effect is found for sales growth in the subset of non-innovators. The results of Bryson (2013) are ambiguous. The study, incorporating data from an employment survey in 1998 and 2004, uses sales per worker and value added per worker as dependent variables as well as two dummy variables that reflect the manager's assessment of the labor productivity and the financial performance of their firms.[31] OLS is used for the analysis of the continuous dependent variables and a probit model for the dummy variables. Depending on the responses, the estimations are conducted with 511 to 599 observations. The results show a significant positive correlation between the use of temporary agency work and the financial performance of firms, but no significant correlation with any of the labor productivity measures.

Two studies analyze the relationship between temporary agency work and firm performance for Spanish industries and firms. Diaz-Mayans and Sanchez (2004) analyzes the technical efficiency of Spanish manufacturing firms using a balanced panel of 180 firms over the 1990 to 2001 period. The analysis is conducted by means of a stochastic frontier approach. It finds a negative relationship between the technical efficiency of Spanish firms and the share of temporary agency worker in total workforce. Ortega and Marchant (2010) use sectoral data for the manufacturing sector, the construction sector, the accommodation sector, the financial intermediation sector and other market services sectors with 102 to 136 observations per industry over the 1987 to 2000 period. The data do not distinguish between TAW and employees with a fixed-term contract. They are jointly considered as temporary workers. Using a two-stage least square approach, the study finds a negative relationship between labor productivity growth and the share of temporary workers, but only for the manufacturing sector.

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[31] The managers are asked to judge whether "labour productivity is a lot better than the industry average" or "financial performance is a lot better than the industry average" (Bryson, 2013, p. 135).

Both Beckmann and Kuhn (2009) and Hirsch and Müller (2012) use the *IAB Establishment Panel* of the *Institute for Employment Research (Institut für Arbeitsmarkt und Berufsforschung*, IAB) to analyze the effect of TAW usage on plant performance in Germany. Both studies use a production function approach with one common production frontier for the entire business economy (i.e. for manufacturing, trade and repair, transport and communication, industrial services (excluding real-estate activities), as well as hotels and restaurants). The dependent variable is sales in Beckmann and Kuhn (2009) and value added in Hirsch and Müller (2012). TAW usage is operationalized firstly by a set of dummy variables for different share categories and, secondly, as a continuous share variable. The share is defined as TAW over total employment. The number of TAW is derived from a snapshot in the IAB survey on June 30th of each year. This, however, might lead to an underestimation of TAW usage because firms might report having no agency workers on the very specific June 30th, but they might actually have used some, many or few, before or after that day. This is very likely due to the short term nature of temporary agency work (Schmidt & Wüllerich, 2011; Antoni & Jahn, 2009).[32] In addition, because data on sales refer to the entire year, there is the possibility that the effect of TAW is not fully captured. Nevertheless, both studies find a significant relationship with firm performance. In Beckmann and Kuhn (2009), OLS, a fixed effects model, and a random effects model are used in analyzing about 25,000 observations over the 2002 to 2005 period. The results point to a nonlinear relationship between temporary agency work and firm performance: the positive effect of temporary agency work shrinks the more it is used. Hirsch and Müller (2012) confirm this finding for the 2003 to 2009 period while applying system GMM.

Finally, Addessi (2014) proposes a structural approach assuming that permanent and temporary labor have different productivity, but are perfect substitutes and that joint labor input is of additive nature. The study focuses on three topics: i) whether the proposed estimation technique is able to provide consistent estimates for the coefficients; ii) whether TAW are actually characterized by a different productivity than permanent employees; and iii) whether the labor composition affect TFP dynamics. The analysis is conducted with a balanced panel of 1,866 Italian manufacturing firms over the 2001 to 2003 period. The results show that productivity between the two types of labor is not significantly different but the use of TAW has a significantly negative effect on TFP dynamics. Also, the author considers it proven that the proposed econometric approach works. In addition, Addessi mentions that value added per worker is positively correlated with the lagged share of permanent labor but negatively correlated with the number of TAW and that ignoring one of these variables in a regression where they should be included, “may induce serious bias in the estimation of the temporary contract coefficient” (Addessi, 2014, p. 668). It is worth adding that this conclusion applies not only to the coefficient of TAW, but also to the remaining coefficients. However, the study does not focus on this topic.

This study deviates from previous studies in four ways: Firstly, it uses a dataset with about 125,000 observations that, unlike the previous German studies, observes TAW usage over the course of the entire year and that focuses on firms instead of plants. Second, this study applies latest econometric developments, namely a structural approach along the lines of ACF, for estimating the production function.[33] Thirdly, we recognize that the production function might not only differ between manufactur-

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[32] Employment duration for more than 50 percent of all temporary agency workers is less than 3 months (Schmidt & Wüllerich, 2011).

[33] This distinction, of course, does not hold with respect to the study of Addessi (2014), which also uses a structural approach. However, the present study assumes a multiplicative nature between the two types of labor along the lines of Haskel and Martin (1993), as it is used, *inter alia*, by Ortega and Marchant (2010), Hirsch and Müller (2012) and Doraszelski and

ing and service industries, but even within the manufacturing industry. Consequently, the analysis is conducted separately for each two-digit manufacturing sector. Finally, the literature review reveals that no study examines the potential bias of productivity estimates or the potential bias of the labor and capital coefficients due to the omission of TAW. This study contributes to the literature by addressing this research gap. It focuses on the question whether TAW is a relevant input factor and whether its omission leads to bias coefficients and biased productivity estimates.

Jaumandreu (2013). This makes it necessary to develop an alternative structural approach than the one proposed by Addessi (2014).

Table A-1: Literature Review

Author(s) (Year)	Unit; Sample Size; Years; Sample type	Country, Industries	Dependent Variable(s)	Modelling of TAW	Econometric Method(s)	Effect of TAW usage
Diaz-Mayans and Sanchez (2004)	Firms; 2,160; 1990 – 2001; panel	Spanish; manufacturing	Log value added	Share of TAW in total workforce	SFA	Negative relationship between technical efficiency and share of TAW in total workforce
Arvanitis (2005)	Firms; 1,382; 1998 – 2000; cross section	Swiss; entire business economy	Log of sales per employee; a dummy for product innovation; a dummy for process innovation	Dummy if temporary work is important for firm	OLS; Probit	No effect on sales per employee; positive and significant for product innovation but insignificant for process innovation
Kleinknecht et al. (2006)	Firms; 590; 1992 – 1994; cross section	Dutch; entire business economy	Sales growth; employment growth	Percentage of hours worked by TAW on total hours worked	OLS	No significant effect
Beckmann and Kuhn (2009)	Plants; 25,000; 2002 – 2005; panel	Germany; entire business economy	Log of sales	Share of TAW on total workforce; squared share of TAW on total workforce; dummy variables for shares for 0%, 1-10%, 11-30%, more than 30%	OLS; FE; RE	Inverse U-shaped relationship between sales and share of TAW in workforce
Ortega and Marchant (2010)	5 Sectors; 16 regions; 680 observations; 1993 – 2000; panel	Spanish; entire business economy	Log value added per worker	Share of TAW in total workforce	2SLS	Negative effect of TAW usage on labor productivity in manufacturing only; no significant effect in other sectors
Hirsch and Müller (2012)	Plants; 25,000; 2003 – 2009; panel	Germany; entire business economy	Log of value added	Share of TAW on total workforce; 9 dummies for shares of 0% to 20%, in steps of 2.5%	OLS; Sys GMM	Inverse U-shaped relationship between value added and share of TAW in workforce

Bryson (2013)	Firms; 511 - 599; 1998-2004; panel and cross section	United Kingdom; entire business economy	Log of sales per worker; log of value added per worker; dummy for managements judgment regarding enhanced labor productivity; dummy for managements judgment regarding enhanced financial performance	Dummy if TAW used by firm; Dummy for TAW use in different occupations within firm	OLS; Probit	No significant correlation between TAW and any labor productivity variable; significant correlation between financial performance and TAW usage
Addessi (2014)	Firms; 1866; 2001-2003; panel	Italy; manufacturing	Log of value added	Share of TAW in total workforce	OLS, NLS, Structural Approach	Significantly negative effect of TAW.

B Deriving the share of TAW in workforce from cost data

As outlined in section 3, the relationship between the number of TAW (L_T) and the number of employees with a permanent contract (L_P) is described by $s_n = L_T/L_P$ or $L_T = s_n L_P$ with $s_n \geq 0$. The subscript n highlights that the share is derived from the observed number of TAW and regular employees. It requires the assumption that there is at least one regular employee in a firm. An almost similar relationship can be derived from the costs for each type of labor:

(11) $$s_c = \frac{c_T L_T}{c_P L_P} = \frac{C_T}{C_P},$$

with c_T capturing the costs per TAW, and c_P the costs per employees with a permanent contract. When multiplied with the number of TAW and the number regular employees, the costs share is derived from the total costs for TAW (C_T) and the total costs for employees with a permanent contract (C_P). In case $c_T = c_P$, the share derived from costs is equal to the share derived from the number workers: $s_n = s_c$; in case $c_T < c_P$, that relationship changes to $s_n > s_c$ and it becomes $s_n < s_c$ if $c_T > c_P$. However, the relationship between the two shares in case $c_T \neq c_P$ can generally be described by:

(12) $$s_n = \frac{s_c}{d},$$

with $d = c_T/c_P$ measuring the differences in costs for TAW compared to an employee with a permanent contract. In other words, the number of TAW can be calculated from cost shares by:

(13) $$L_T = \frac{s_c}{d} L_P.$$

c_T and c_P either need to be observed or we have to make a qualified estimate about d. In the latter case, we have to recognize that c_P is mostly, but not only, the gross wage of employee with a permanent contract. Hence, it mainly cover the gross wage including the statutory social costs. However, it also has to capture all other social costs that a firm might grant. This can be allowances and subsidies in case of illness, for recreation and spa stays, expenses for the company pension scheme, etc. Such additional benefits are observed within the CSS dataset. For an exhaustive list we refer interested reader to the metadata for the CSS (Statistisches Bundesamt, 2015a).

The cost for a TAW, on the other hand, is significantly more than just the gross wage cost of the temporary agency worker. Instead, the client firm pays a fee that also covers additional risks, costs and potential profit of the temporary work agency. A classical risk for temporary work agency is, *inter alia*, that they have to pay TAW that have been sent back from client firms until the temporary work agency have found new client firms for these “unneeded” TAW, or, in case they do not find a new client firm in time, until they can lay them off. In addition, temporary agency firms have to pay their own staff, they have to pay for offices, and must cover other variable costs. Finally, and after all, temporary work agencies aim at making profits. Hence, in order to cover all these costs, risks and in order to make a profit, the fee client firms charge is usually considerably larger than the gross wage of TAW. Conversely, it also follows that the cost per TAW for client firms is usually much larger than the gross wage of the TAW.

In the current dataset we observe C_P and C_T. Hence, we have to make a qualified estimate about d. For this purpose we use the existing literature on wage gaps, thus the difference between the gross wage of the TAW and their colleagues with permanent contracts, and the differences between the fee paid by the client firm and the actual gross wage of the TAW. Table B-2 shows the wage gaps identified by different studies. As can be seen, the wage gap varies over time, from country to country and across industries. For Germany we see wage gaps between 5% and 50%.

Table B-2: Average wage gaps in the literature

study	wage gap(s)	country	industries	period
Nollen (1996)	+37% – 45%	USA	across industries	1989,1994
Kvasnicka and Werwatz (2002)	10%– 40%	Germany	across industries	1975 – 1995
Jahn and Rudolph (2002)	0% – 15%	Spain	across industries	1999, 2002
	0% – 32%	United Kingdom	across industries	1999, 2002
	5% – 30%	Austria	across industries	2002
	22% – 40%	Germany	across industries	2002
Houseman et al. (2003)	17% – 40%	USA	car manufacturing; health service	1999, 2000
Burda and Kvasnicka (2006)	5% – 45%	Germany	across industry	1973 – 2004
Ford et al. (2008)	4% – 36%	United Kingdom	across industries	2000
Ford and Slater (2008)	9% – 11%	United Kingdom	service sector	2000
Oberst et al. (2008)	29% – 50%	Germany	service sector	2005
Antoni and Jahn (2009)	31%	Germany	across industries	1997 – 2004
Jahn (2010)	38% – 45%	Germany	across industries	1997 – 2004

Less information is available with respect to the difference between the wage of a TAW and the fee the client firm pays to the temporary work agency. Rangnitz (2008) states for Germany that 2/3 of what is paid by the client firm to the temporary agency covers the gross wages of the TAW, while 1/3 covers the agency's overhead and profit. The study by Kvasnicka (2005) finds that the fees paid by the client firms are on average 144% larger than the gross wages of the TAW, with a range of, depending on the occupation, 130% to 160%. Nollen (1996) reports evidence from case studies that total labor costs for TAW are between 0% and 14% lower than the costs for core worker.

Houseman (2001) does not report concrete differences between fees and wages for TAW or the differences between costs for TAW and costs for workers with permanent contracts. However, the study finds that hourly pay costs for TAW is higher or about the same as the hourly pay cost for regular employees in 83.9% of the establishments in the sample. Even when comparing the costs for TAW with the "hourly pay plus benefits cost of regular employees in similar positions" (Houseman, 2001, p. 159), 57.7% of the establishments still report higher or equal costs for TAW.

Kleinknecht et al. (2006) analyze, *inter alia*, to what degree different types of employment leads to costs savings for firms. Although the study does not provide data on difference between TAW wages and fees for TAW usage, the analysis reveals that different types of "flexible contracts lead to significant savings … [This] does not, however, hold for people hired from manpower agencies" (Kleinknecht, et al., 2006, p. 176). Hence, the studies by Houseman (2001) and Kleinknecht et al. (2006) support the assumption the TAW are often as costly as worker with permanent contracts.

We use these findings and the findings about wage gaps to calculate the maximum and the minimum discount factor (d). For the lower bound, which would be the maximum cost saving difference, we use the maximum wage gap from the literature. According to Jahn (2010) and Oberst et al. (2008) the maximum wage gap is roughly 50%. When we assume that TAW receive only half as much as their colleagues in the client firm and that the fee payed by the client firms is without any mark-up and just covers the gross wages of TAW, the minimum discount factor would be 0.5 ($d = 0.5$). In this scenario firms would generate the highest cost savings from TAW usage.

The upper bound uses the findings by Kvasnicka (2005) and Rangnitz (2008). According to Kvasnicka (2005), the average fee is in a range between 130% and 160%, with a mean of 144%. With these mark-ups we can calculate the potential discount factor for a given wage gap by

$$w_P \times (1 - gap) = w_T$$

(14) $$w_T \times mark - up = c_T, \text{ leading to}$$

$$d = c_T / c_p$$

with w_P as gross wage of employees with a permanent contract, w_T as gross wage of TAW, gap measuring the wage gap between these two types of workers and $mark - up$ measuring the percentage difference between the gross wage of a TAW and the fee the temporary work agency charges. For simplicity we assume here $w_P = c_P$.

Table B-3: Discount factors for different wage gaps and mark ups

		mark-up							
		130%	135%	140%	145%	150%	155%	160%	row means
wage gap	0%	1.30	1.35	1.40	1.45	1.50	1.55	1.60	**1.45**
	5%	1.24	1.28	1.33	1.38	1.43	1.47	1.52	1.38
	10%	1.17	1.22	1.26	1.31	1.35	1.40	1.44	1.31
	15%	1.11	1.15	1.19	1.23	1.28	1.32	1.36	1.23
	20%	1.04	1.08	1.12	1.16	1.20	1.24	1.28	1.16
	25%	0.98	1.01	1.05	1.09	1.13	1.16	1.20	1.09
	30%	0.91	0.95	0.98	1.02	1.05	1.09	1.12	1.02
	35%	0.85	0.88	0.91	0.94	0.98	1.01	1.04	0.94
	40%	0.78	0.81	0.84	0.87	0.90	0.93	0.96	0.87
	45%	0.72	0.74	0.77	0.80	0.83	0.85	0.88	0.80
	50%	0.65	0.68	0.70	0.73	0.75	0.78	0.80	0.73
column means		0.98	1.01	1.05	1.09	1.13	1.16	1.20	**1.09**

Using different assumption about the wage gap and the differences between the fee and the wage gap, we can calculate diverse discount factors. E.g., if we assume that TAW and worker with permanent contracts would receive the same gross wage, so if there were a wage gap of 0%, the maximum d would be 1.6. In case there is a wage gap of 5%, 10%, 20%, 30%, 40% or 50%, and using the maximum markup of 160% on TAW wages, the discount factor would become 1.5, 1.4, 1.3, 1.1, 1 and 0.8. Additional calculations with every mark-up between 130% and 160% and every wage gap from the literature can be conducted as shown in Table B-3. From these calculations we derive the maximum discount factor of $d = 1.5$. Hence, we assume for this scenario that there is no wage gap between TAW and employees with a permanent contract but that temporary work agencies charge a fee that is between 130% and 160% above the gross wage of TAW. In other words: in this scenario firms would have 50% higher costs when using a TAW compared to an employee with a permanent contract. Slightly lower values for the upper bound of d are derived when using the finding of Rangnitz (2008), who stated that in Germany, on average, 2/3 of what is paid by the client firm to the temporary work agency covers gross wages of the TAW, while 1/3 covers the agency's overhead and profit.

Summing up, the two extremes are $d = 0.5$ and $d = 1.5$. The "true" but unknown cost difference (d) will be somewhere in between with near certainty. Consequently, if we use these extreme values for calculating the number of TAW in the firms and still find significant results, it is almost certain that the effect will also be found with the "true" but unknown cost difference. Moreover, the reader should also take note of the fact that the discount factor d is close to 1 one average in many scenarios in Table B-3. In fact, the lower the actual mark up, the more the average d tends towards 1. This is in line with the findings of Kleinknecht et al. (2006) and partly also with Houseman (2001).

Finally, for checking whether the number of TAW that is estimated this way is reasonable, we compare the calculated number of TAW with the number of TAW hired with manufacturing related occupations. The latter data can be obtained from the *statistic on temporary employment.*[34] The comparison is limited to the period 2008 - 2011, because projection factors for labor in the cost structure census are available only from 2008 onward. In addition, the occupation classification system used by the statistical offices changed between 2010 and 2011. Due to that change, we must use different occupations in 2011 compared to the 2008 to 2010 period.

Before 2011, the following occupation list was used by the statistical offices: *Worker in chemicals & plastics manufacturing; Metal worker; Fitter, mechanics and similar professions; Electrician; Assembly workers & other metalworking occupations; Construction occupations; Interior decorators, upholsterers; Unskilled worker / manual worker; Other production related occupations; Technical Jobs; Merchant professions; Organizational, administrative, clerical occupations; Health service occupations; General service occupations; Other service occupations; Other professions*.[35] From this list of occupations we added up the number of TAW for the 2008 to 2010 period for *Chemicals & plastics trade; Metal worker; Fitter, mechanics and similar professions; Assembly workers & other metalworking occupations; Other production related occupations* and *Technical Jobs.* After 2011, the following occupation list applies: *Agriculture, forestry, animal agriculture, horticulture occupations; Metal production, metal processing, metal work occupations; Mechanical engineering professions and automotive engineering professions; Mechatronics, energy occupations u. electrical occupations; Food processing occupations; Others professions (raw material extraction, production, manufacturing); Construction,*

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[34] Data are taken from „Arbeitsmarkt in Zahlen – Arbeitnehmerüberlassung, Statistik der Bundesagentur für Arbeit, Arbeitnehmerüberlassung, Leiharbeitnehmer und Verleihbetriebe, Nürnberg".
It can be assessed under http://statistik.arbeitsagentur.de/Navigation/Statistik/Statistik-nach-Themen/Beschaeftigung/Arbeitnehmerueberlassung/Arbeitnehmerueberlassung-Nav.html.

[35] The original German terms for the different occupations that TAW are assigned to until 2010 are:
Chemiearbeiter & Kunststoffverarbeiter; Metallerzeuger & -bearbeiter; Schlosser, Mechaniker u. zugeordnete Berufe; Elektriker; Montierer & Metallberufe, a.n.g.; Bauberufe; Bau-, Raumausstatter, Polsterer; Hilfsarbeiter ohne nähere Tätigkeitsangabe; Übrige Fertigungsberufe; Technische Berufe; Warenkaufleute; Organisations-,Verwaltungs-,Büroberufe; Gesundheitsdienste &-berufe; Allgemeine Dienstleistungsberufe; Übrige Dienstleistungsberufe; Sonstige Berufe.

architecture, surveying, building services occupations; Natural science, geography, computer science professions; Transport and logistic (excluding vehicle drivers) occupations; vehicle drivers; Protection, security, monitoring professions; Cleaning occupations; Commercial services, trade, distribution, tourism; Business organization, accounting, legal, administrative professions; Health, social services, teaching and education occupations; Human sciences, culture, design professions.[36] From this list of occupations we added up the number of TAW for 2011 with the occupations *Metal production, metal processing, metal work occupations; Mechanical engineering professions and automotive engineering professions; Mechatronics, energy occupations; Food processing occupations.* The resulting number of TAW is shown in row three of Table B-4.

It is well known that many of the TAW that are hired as *unskilled workers* actually work in the manufacturing industries. For a rough estimate we add this TAW to the number of TAW with manufacturing professions The same applies to e*lectrical occupations,* which are used by machinery firms, automotive firms etc., but also by construction firms. However, given that precise information is missing in the *statistic on temporary employment*, we assume that at least half of these TAW are working in the manufacturing industries. Adding these two professions increases the number of TAW considerably as shown in row four of Table B-4.

We compare these numbers of TAW in the manufacturing related professions, derived from an external source, with the number of TAW derived from the cost structure census. This allows us to determine whether our approach leads to reasonable estimates for the number of TAW. As Table B-4 shows, the estimated number of TAW using costs and a $d = 1$ is relatively close to the number of TAW hired by temporary employment agencies to work in manufacturing-related professions. When enlarging the set of occupations to those we consider as mainly used in manufacturing, as described above, we have roughly the same number of TAW when we use a d between 0.65 and 0.60.

These figures and the previously illustrated wage gaps and mark-ups reveal three things. First, using the cost shares derived from the cost structure census and applying the above outlined approach lead to estimated numbers of TAW which are, regardless of the “true” but unknown cost differences, close to the observed number of TAW with manufacturing related professions from an external source. Second, the assumption of $d = 1$ is quite conservative but finds support from the literature (Kleinknecht, et al., 2006; Houseman, 2001) and the calculated number of TAW with $d = 1$ is in line with the number of TAW that work in purely manufacturing related professions; professions that are almost certainly only used in manufacturing firms. Third, even if we are more generous and consider TAW with less specific professions as being worker in the manufacturing sector, the resulting number of TAW is still within the range of the number of TAW calculated when using discount factors in the range of $d = 0.5$ and $d = 1.5$. In fact, the calculations show that the "true" but unknown value for d is most likely smaller than one.

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[36] The original German term for the different occupations that TAW are assigned to since 2011, are:
Land-, Forst-, Tierwirtsch, Gartenbau; Metallerzeugung, -bearbeitung, Metallbau; Maschinen- und Fahrzeugtechnikberufe; Mechatronik-, Energie- u. Elektroberufe; Lebensmittelherstellung u. –verarbeitung; Übr. Berufe (Rohstoffgewinnung, Produktion, Fertigung); Bau, Architektur, Vermessung, Gebäudetechnik; Naturwissenschaft, Geografie, Informatik; Verkehr, Logistik (außer Fahrzeugführer); Führer von Fahrzeug- u. Transportgeräten; Schutz-, Sicherheits-, Überwachungsberufe; Reinigungsberufe; Kaufmännische Dienstleistungen, Handel, Vertrieb, Tourismus; Unternehmensorganisation, Buchhaltung, Recht, Verwaltung; Gesundheit, Soziales, Lehre u. Erziehung; Geisteswissenschaften, Kultur, Gestaltung.

In summary, the estimated number of temporary workers with method employed in this study is supported by external data and the previous literature.

Table B-4: Comparison between estimated number of TAW and reported number of TAW in manufacturing related occupations

		Year			
		2008	2009	2010	2011
	Total number of TAW	733,129	621,067	814,802	871,656
	No. of TAW in manufact. related professions[a]	211,704	165,878	208,673	281,887
	No. of TAW in manufact. related professions incl. half of all unskilled TAW and electrician[b]	350,627	274,098	366,077	412,706
calculated number of TAW using a d of	0.50	474,641	328,467	433,378	540,548
	0.55	431,492	298,606	393,980	491,408
	0.60	395,534	273,722	361,149	450,457
	0.65	**365,108**	**252,667**	**333,368**	**415,806**
	0.70	339,029	234,619	309,556	386,106
	0.75	316,427	218,978	288,919	360,366
	0.80	296,651	205,292	270,861	337,843
	0.85	279,201	193,216	254,928	317,970
	0.90	263,689	182,482	240,766	300,305
	0.95	249,811	172,877	228,094	284,499
	1.00	**237,320**	**164,233**	**216,689**	**270,274**
	1.05	226,020	156,413	206,371	257,404
	1.10	215,746	149,303	196,990	245,704
	1.15	206,366	142,812	188,425	235,021
	1.20	197,767	136,861	180,574	225,229
	1.25	189,856	131,387	173,351	216,219
	1.30	182,554	126,333	166,684	207,903
	1.35	175,793	121,654	160,511	200,203
	1.40	169,515	117,310	154,778	193,053
	1.45	163,669	113,264	149,441	186,396
	1.50	158,214	109,489	144,459	180,183

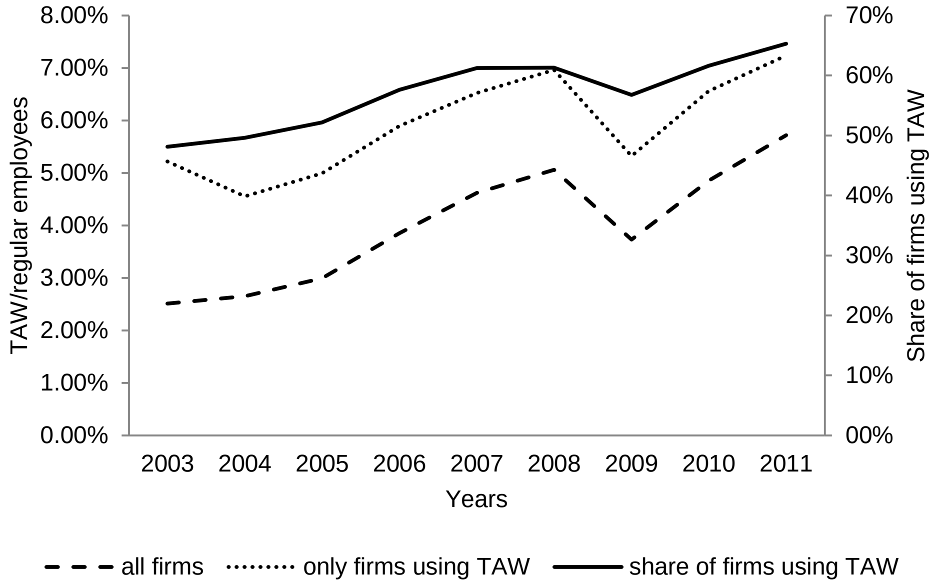
Sources: *monthly report in the manufacturing sector, labor market in numbers*, own calculations.

a: *Metal production, metal processing, metal work occupations; Mechanical engineering professions and automotive engineering professions; Mechatronics, energy occupations; Food processing occupations.*

b: Metal production, metal processing, metal work occupations; Mechanical engineering professions and automotive engineering professions; Mechatronics, energy occupations u. ½ of electrical occupations; Food processing occupations; Unskilled worker

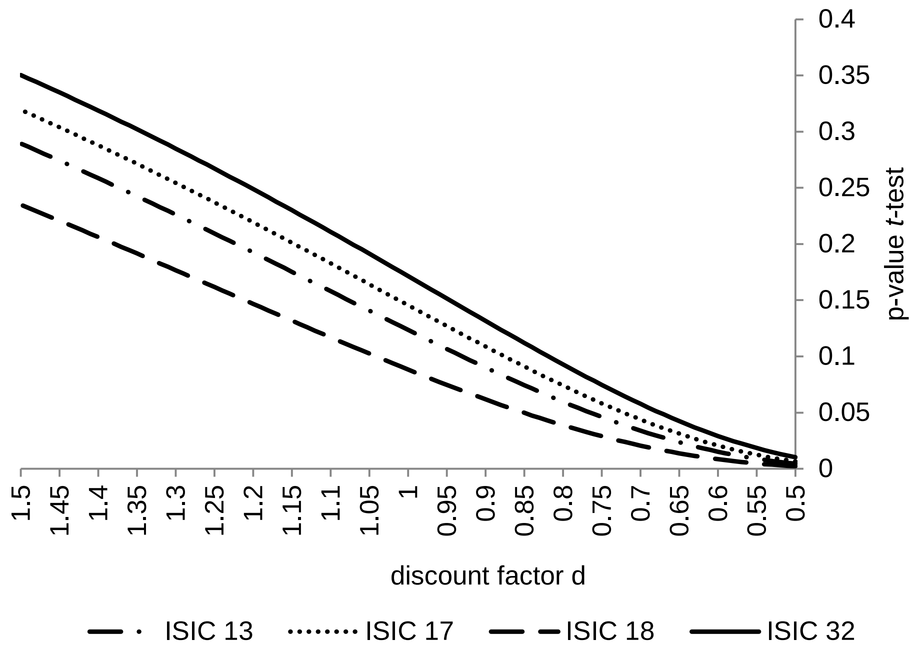
C Graphs

Figure 4: TAW usage by German manufacturing firms, before any data cleaning



Source: *cost structure survey*; own calculations

Figure 5: p-value for *t*-tests on difference in labor productivity for different values of *d*; selected 2-digit manufacturing industries[37]



Source: *cost structure survey*; own calculations

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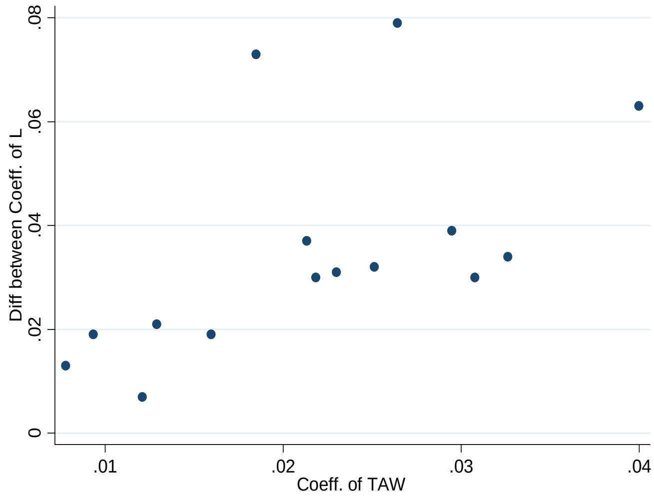
[37] Industry *ISIC 18* is included because the difference is significant only at the 10 percent level for $d = 1$.

Figure 6: Coefficients of TAW in comparison with the differences in the labor coefficients



Source: *cost structure survey*; own calculations

D Descriptive statistics and result tables

Table D-5: Descriptive statistics of dependent and independent variables

Variables		Mean	Std. Dev.	Observations	
Value added (1000 Euro)	overall	14,838.32	31,444.73	N=	125,526
	between		26,722.29	n=	26,463
	within		8,279.27	T-bar=	4.7435
Capital (1000 Euro)	overall	41,897.53	113,759.50	N=	125,526
	between		97,166.06	n=	26,463
	within		32,599.64	T-bar=	4.7435
Material (1000 Euro)	overall	23,201.75	57,566.29	N=	125,526
	between		50,300.23	n=	26,463
	within		14,962.72	T-bar=	4.7435
Labor	overall	222.60	375.12	N=	125,526
	between		324.48	n=	26,463
	within		61.16	T-bar=	4.7435
TAW	overall	8.72	27.70	N=	125,526
	between		22.23	n=	26,463
	within		13.14	T-bar=	4.7435

Source: *cost structure survey*; own calculations

Table D-6: Descriptive statistic for ratio of temporary agency workers to core workforce

ISIC 4 sector names	industry code	Entire Dataset mean	Std. Dev.	5% pctl.	95% pctl.	N	Only Observations Using TAW mean	Std. Dev.	5% pctl.	95% pctl.	N
Manufacturing	10t33	3.50%	7.11%	0	16.59%	125,526	5.95%	8.45%	0.14%	22.84%	73,730
Manuf. of food prod.	10	3.45%	8.09%	0	19.40%	14,263	7.92%	10.70%	0.18%	30.48%	6,221
Manuf. of beverages	11	2.50%	5.21%	0	11.97%	2,249	4.88%	6.44%	0.15%	16.86%	1,152
Manuf. of textiles	13	1.66%	4.34%	0	8.73%	3,512	3.85%	5.94%	0.08%	13.25%	1,512
Manuf. of wearing apparel	14	0.42%	1.95%	0	2.25%	1,985	2.17%	3.96%	0.04%	8.17%	388
Manuf. of leather & related prod.	15	1.94%	4.94%	0	11.51%	930	5.19%	6.95%	0.10%	18.54%	348
Manuf. of wood & prod. of wood etc.	16	3.06%	6.31%	0	14.49%	3,274	5.60%	7.67%	0.17%	21.27%	1,788
Manuf. of paper & paper prod.	17	2.12%	4.24%	0	9.53%	3,415	3.43%	4.95%	0.10%	12.96%	2,117
Printing & reprod. of recorded media	18	2.21%	6.30%	0	11.33%	2,914	5.47%	8.96%	0.09%	24.57%	1,179
Manuf. of chemicals & chemical prod.	20	2.75%	5.69%	0	12.47%	6,492	4.15%	6.57%	0.13%	16.21%	4,300
Manuf. of basic pharmaceutical prod. & pharmaceutical preparations	21	2.40%	5.23%	0	9.75%	1,588	4.02%	6.28%	0.12%	13.70%	947
Manuf. of rubber & plastics prod.	22	3.95%	6.73%	0	16.59%	7,540	5.79%	7.47%	0.14%	19.98%	5,154
Manuf. of other non-metallic mineral prod.	23	3.13%	6.53%	0	14.33%	6,469	5.28%	7.79%	0.16%	19.05%	3,826
Manuf. of basic metals	24	3.91%	6.80%	0	16.85%	4,929	5.69%	7.57%	0.13%	20.45%	3,386
Manuf. of fabricated metal prod., except machinery & equipment	25	4.20%	7.80%	0	18.67%	15,399	6.51%	8.90%	0.17%	24.27%	9,937
Manuf. of computer, electronic & optical prod.	26	2.71%	5.92%	0	12.76%	6,218	4.85%	7.23%	0.12%	17.75%	3,479
Manuf. of electrical equipment	27	3.78%	7.06%	0	17.40%	7,453	5.84%	8.06%	0.14%	22.07%	4,820
Manuf. of machinery & equipment	28	3.59%	6.73%	0	15.96%	19,701	5.44%	7.65%	0.15%	20.20%	13,018
Manuf. of motor vehicles, trailers & semi-trailers	29	5.60%	8.80%	0	22.89%	5,285	7.82%	9.53%	0.21%	27.21%	3,784
Manuf. of other transport equipment	30	6.58%	9.91%	0	27.58%	1,492	9.29%	10.65%	0.26%	34.17%	1,057
Manuf. of furniture	31	3.07%	6.33%	0	14.99%	3,012	5.43%	7.61%	0.12%	20.46%	1,705
Other Manuf.	32	1.46%	3.76%	0	7.96%	4,428	3.95%	5.34%	0.10%	13.95%	1,636
Repair & installation of machinery & equipment	33	8.48%	12.86%	0	37.79%	2,978	12.78%	13.94%	0.31%	44.10%	1,976

Source: *cost structure survey*; own calculations

Table D-7: Coefficients OLS estimation of the production function

Ind. Code	T		L		K		Constant		N	R^2
10t33	0.0062***	(0.0017)	0.876***	(0.0038)	0.160***	(0.0022)	8.931***	(0.026)	35,909	0.871
			0.881***	(0.0035)	0.160***	(0.0022)	8.912***	(0.026)	35,909	0.871
10	-0.0005	(0.0062)	0.692***	(0.0140)	0.289***	(0.00869)	7.548***	(0.113)	3,323	0.802
			0.691***	(0.0128)	0.289***	(0.00868)	7.549***	(0.110)	3,323	0.802
11	0.123***	(0.0202)	0.746***	(0.0597)	0.124***	(0.0410)	10.42***	(0.514)	592	0.677
			0.838***	(0.0594)	0.153***	(0.0420)	9.630***	(0.513)	592	0.657
13	0.0359***	(0.0091)	0.822***	(0.0246)	0.186***	(0.0152)	8.794***	(0.163)	698	0.877
			0.830***	(0.0248)	0.195***	(0.0152)	8.654***	(0.161)	698	0.874
14	0.0610**	(0.0252)	0.668***	(0.0831)	0.253***	(0.0552)	8.703***	(0.557)	153	0.841
			0.756***	(0.0760)	0.248***	(0.0560)	8.369***	(0.548)	153	0.835
15	-0.0038	(0.0158)	0.694***	(0.0576)	0.253***	(0.0290)	8.476***	(0.273)	167	0.859
			0.690***	(0.0555)	0.254***	(0.0288)	8.477***	(0.272)	167	0.859
16	0.0255***	(0.0097)	0.802***	(0.0229)	0.196***	(0.0129)	8.667***	(0.140)	822	0.894
			0.819***	(0.0221)	0.201***	(0.0128)	8.556***	(0.134)	822	0.893
17	0.0045	(0.0090)	0.745***	(0.0220)	0.263***	(0.0138)	7.769***	(0.161)	1,080	0.891
			0.748***	(0.0212)	0.263***	(0.0138)	7.758***	(0.159)	1,080	0.891
18	-0.0324***	(0.0101)	0.968***	(0.0267)	0.135***	(0.0153)	8.780***	(0.183)	482	0.912
			0.939***	(0.0254)	0.133***	(0.0154)	8.916***	(0.180)	482	0.910
20	-0.0200***	(0.0070)	0.796***	(0.0165)	0.239***	(0.0106)	8.151***	(0.134)	2,321	0.851
			0.778***	(0.0153)	0.239***	(0.0106)	8.218***	(0.133)	2,321	0.850
21	-0.0061	(0.0158)	1.013***	(0.0387)	0.102***	(0.0225)	9.417***	(0.269)	496	0.858
			1.006***	(0.0338)	0.102***	(0.0224)	9.436***	(0.264)	496	0.858
22	-0.0026	(0.0052)	0.859***	(0.0122)	0.182***	(0.0079)	8.502***	(0.094)	2,424	0.916
			0.857***	(0.0116)	0.182***	(0.0079)	8.509***	(0.093)	2,424	0.916
23	0.0104	(0.0065)	0.774***	(0.0152)	0.243***	(0.0098)	8.016***	(0.116)	1,981	0.898
			0.782***	(0.0143)	0.243***	(0.0098)	7.989***	(0.114)	1,981	0.897
24	-0.0016	(0.0073)	0.786***	(0.0189)	0.210***	(0.0113)	8.577***	(0.134)	1,787	0.851
			0.785***	(0.0179)	0.210***	(0.0113)	8.582***	(0.132)	1,787	0.851
25	-0.0038	(0.0040)	0.918***	(0.0098)	0.145***	(0.0060)	8.921***	(0.068)	4,376	0.911
			0.915***	(0.0093)	0.145***	(0.0060)	8.934***	(0.066)	4,376	0.911
26	-0.0085	(0.0094)	0.864***	(0.0240)	0.206***	(0.0157)	8.187***	(0.179)	1,639	0.835
			0.859***	(0.0233)	0.204***	(0.0155)	8.233***	(0.172)	1,639	0.835
27	0.0243***	(0.0058)	0.879***	(0.0152)	0.152***	(0.0098)	9.028***	(0.106)	2,331	0.907
			0.895***	(0.0147)	0.155***	(0.0098)	8.943***	(0.105)	2,331	0.906
28	0.0331***	(0.0036)	0.921***	(0.0095)	0.112***	(0.0062)	9.572***	(0.068)	6,194	0.904
			0.952***	(0.0090)	0.112***	(0.0063)	9.463***	(0.068)	6,194	0.903
29	0.0191**	(0.0076)	0.854***	(0.0166)	0.163***	(0.0103)	8.793***	(0.129)	1,937	0.870
			0.869***	(0.0156)	0.165***	(0.0103)	8.737***	(0.127)	1,937	0.869
30	0.0139	(0.0150)	0.853***	(0.0379)	0.188***	(0.0255)	8.751***	(0.267)	607	0.879
			0.869***	(0.0338)	0.188***	(0.0255)	8.701***	(0.262)	607	0.879
31	0.0281***	(0.0089)	0.881***	(0.0233)	0.129***	(0.0145)	9.374***	(0.150)	756	0.906
			0.900***	(0.0226)	0.133***	(0.0146)	9.261***	(0.147)	756	0.905
32	0.0175	(0.0110)	0.851***	(0.0265)	0.225***	(0.0174)	8.101***	(0.185)	771	0.906
			0.859***	(0.0260)	0.230***	(0.0171)	8.003***	(0.174)	771	0.905
33	0.0129	(0.0079)	0.998***	(0.0192)	0.101***	(0.0140)	9.407***	(0.148)	972	0.927
			1.010***	(0.0175)	0.0999***	(0.0140)	9.384***	(0.147)	972	0.926

Source: *cost structure survey*; *** p<0.01, ** p<0.05, * p<0.1; Standard errors in parentheses

Table D-8: Structural estimation of the production function with and without TAW, basis model

with TAW

Ind. Code	N	T (Std.Err)		L (Std.Err)		K (Std.Err)		Hansen-Test Chi2-value	df	p-value
10t33	35,909	0.008***	(0.0008)	0.85***	(0.0048)	0.105***	(0.0025)	149.58***	4	0.00
10	3,323	-0.016**	(0.0061)	0.687***	(0.0157)	0.197***	(0.0154)	9.5**	4	0.05
11	592	0.052	(0.0423)	0.681***	(0.0641)	0.197***	(0.0324)	2.98	4	0.56
13	698	0.025***	(0.0061)	0.813***	(0.0217)	0.119***	(0.0071)	12.27**	4	0.02
14	153	0.008	(0.0514)	0.668***	(0.0806)	0.33***	(0.044)	4.72	4	0.32
15	167	-0.067	(0.0666)	0.867***	(0.1107)	0.112**	(0.0359)	0.38	4	0.98
16	822	0.039***	(0.0064)	0.743***	(0.0322)	0.069***	(0.0142)	8.55*	4	0.07
17	1,080	0.025***	(0.004)	0.717***	(0.0183)	0.205***	(0.0098)	5.76	4	0.22
18	482	-0.014	(0.0128)	0.884***	(0.03)	0.097***	(0.011)	4.56	4	0.34
20	2,321	0.031***	(0.0067)	0.715***	(0.0242)	0.182***	(0.0115)	7.52	4	0.11
21	496	-0.094	(0.1816)	1.19***	(0.2345)	0.021	(0.045)	3.35	4	0.50
22	2,424	0.013**	(0.005)	0.788***	(0.0184)	0.117***	(0.0144)	10.08**	4	0.04
23	1,981	0.022***	(0.0044)	0.78***	(0.0226)	0.162***	(0.0206)	2.55	4	0.64
24	1,787	0.017***	(0.004)	0.776***	(0.0248)	0.139***	(0.0107)	14.7***	4	0.01
25	4,376	0.009***	(0.0022)	0.833***	(0.0117)	0.087***	(0.0079)	18.86***	4	0.00
26	1,639	0.001	(0.0074)	0.849***	(0.0169)	0.164***	(0.0085)	13.78***	4	0.01
27	2,331	0.026***	(0.0024)	0.817***	(0.0231)	0.118***	(0.0102)	3.9	4	0.42
28	6,194	0.029***	(0.003)	0.938***	(0.0117)	0.077***	(0.0046)	41.95***	4	0.00
29	1,937	0.021***	(0.0036)	0.71***	(0.0357)	0.093***	(0.0123)	6.2	4	0.19
30	607	0.009	(0.0103)	0.885***	(0.0267)	0.134***	(0.0077)	4.14	4	0.39
31	756	0.016**	(0.0052)	0.851***	(0.0208)	0.111***	(0.0127)	1.09	4	0.90
32	771	0.012*	(0.006)	0.81***	(0.0319)	0.149***	(0.0176)	6.93	4	0.14
33	972	0.033*	(0.0131)	0.978***	(0.0235)	0.06***	(0.0096)	1.68	4	0.79

without TAW

Ind. Code	N	L (Std.Err)		K (Std.Err)		Hansen-Test Chi2-value	df	p-value
10t33	35,909	0.863***	(0.0047)	0.107***	(0.0025)	141.98***	3	0.00
10	3,323	0.676***	(0.0149)	0.199***	(0.0156)	7.74*	3	0.05
11	592	0.741***	(0.0488)	0.195***	(0.0349)	1.88	3	0.60
13	698	0.869***	(0.0237)	0.120***	(0.0075)	16.42***	3	0.00
14	153	0.682***	(0.0708)	0.310***	(0.047)	3.61	3	0.31
15	167	0.761***	(0.0302)	0.152***	(0.029)	3.27	3	0.35
16	822	0.800***	(0.0268)	0.070***	(0.0145)	6.99*	3	0.07
17	1,080	0.749***	(0.015)	0.203***	(0.0103)	4.61	3	0.20
18	482	0.843***	(0.0261)	0.109***	(0.0106)	0.72	3	0.87
20	2,321	0.745***	(0.0231)	0.171***	(0.0105)	7.84**	3	0.05
21	496	1.016***	(0.0689)	0.039	(0.0408)	4.01	3	0.26
22	2,424	0.809***	(0.0152)	0.124***	(0.0143)	8.49**	3	0.04
23	1,981	0.811***	(0.0205)	0.161***	(0.0202)	0.45	3	0.93
24	1,787	0.812***	(0.0212)	0.136***	(0.0105)	12.18***	3	0.01
25	4,376	0.852***	(0.0104)	0.091***	(0.008)	13.41***	3	0.00
26	1,639	0.837***	(0.0158)	0.166***	(0.0079)	12.69***	3	0.01
27	2,331	0.896***	(0.0215)	0.124***	(0.0101)	2.21	3	0.53
28	6,194	0.976***	(0.011)	0.075***	(0.0047)	27.63***	3	0.00
29	1,937	0.747***	(0.0397)	0.096***	(0.0126)	6.44*	3	0.09
30	607	0.886***	(0.0182)	0.133***	(0.0081)	4.97	3	0.17
31	756	0.870***	(0.0202)	0.109***	(0.0131)	0.02	3	1.00
32	771	0.817***	(0.0265)	0.154***	(0.0174)	7.38*	3	0.06
33	972	1.012***	(0.0178)	0.067***	(0.01)	3.26	3	0.35

Source: *cost structure survey*; *** p<0.01, ** p<0.05, * p<0.1; Standard errors in parentheses

Table D-9: Structural estimation of the production function for $d = 0.5$ and $d = 1.5$

Ind. Code	N	T (Std.Err)		L (Std.Err)		K (Std.Err)		Hansen-Test		
								Chi2-value	df	p-value
					$d = 0.5$					
10t33	35,909	0.004***	(0.0003)	0.85***	(0.0047)	0.105***	(0.0025)	149.58***	4	0.00
10	3,323	-0.006	(0.0033)	0.671***	(0.0202)	0.228***	(0.0320)	8.06**	3	0.04
11	592	0.026	(0.0211)	0.681***	(0.0641)	0.197***	(0.0324)	2.98	4	0.56
13	698	0.011***	(0.0032)	0.789***	(0.0228)	0.187***	(0.0244)	1.91	3	0.59
14	153	0.004	(0.0256)	0.667***	(0.0806)	0.33***	(0.0440)	4.7	4	0.32
15	167	-0.013	(0.0100)	0.807***	(0.0458)	0.133***	(0.0223)	1.44	6	0.96
16	822	0.020***	(0.0032)	0.735***	(0.0307)	0.074***	(0.0144)	9.61	6	0.14
17	1,080	0.013***	(0.002)	0.717***	(0.0182)	0.205***	(0.0098)	5.76	4	0.22
18	482	-0.007	(0.0063)	0.884***	(0.0300)	0.097***	(0.0109)	4.56	4	0.34
20	2,321	0.015***	(0.0033)	0.715***	(0.0242)	0.182***	(0.0114)	7.52	4	0.11
21	496	0.009	(0.0113)	1.023***	(0.0566)	0.050	(0.0327)	7.28	9	0.61
22	2,424	0.006**	(0.0024)	0.788***	(0.0183)	0.117***	(0.0144)	10.08**	4	0.04
23	1,981	0.011***	(0.0021)	0.78***	(0.0225)	0.162***	(0.0205)	2.55	4	0.64
24	1,787	0.009***	(0.0020)	0.88***	(0.0291)	0.136***	(0.0105)	12.52**	4	0.01
25	4,376	0.005***	(0.0011)	0.833***	(0.0116)	0.087***	(0.0078)	18.86***	4	0.00
26	1,639	0.001	(0.0039)	0.808***	(0.0224)	0.199***	(0.0149)	7.11*	3	0.07
27	2,331	0.013***	(0.0011)	0.817***	(0.0231)	0.118***	(0.0102)	3.9	4	0.42
28	6,194	0.015***	(0.0014)	0.938***	(0.0117)	0.077***	(0.0046)	41.95***	4	0.00
29	1,937	0.011***	(0.0017)	0.71***	(0.0357)	0.093***	(0.0122)	6.19	4	0.19
30	607	0.004	(0.0051)	0.885***	(0.0267)	0.134***	(0.0077)	4.14	4	0.39
31	756	0.008**	(0.0026)	0.851***	(0.0207)	0.111***	(0.0126)	1.09	4	0.90
32	771	0.006*	(0.003)	0.81***	(0.0318)	0.149***	(0.0175)	6.93	4	0.14
33	972	0.016*	(0.0065)	0.978***	(0.0235)	0.059***	(0.0096)	1.68	4	0.79
					d=1.5					
10t33	35,909	0.012***	(0.0011)	0.850***	(0.0047)	0.105***	(0.0025)	149.58***	4	0.00
10	3,323	-0.019	(0.0100)	0.671***	(0.0202)	0.228***	(0.032)	8.06**	3	0.04
11	592	0.078	(0.0632)	0.681***	(0.0640)	0.197***	(0.0324)	2.98	4	0.56
13	698	0.034***	(0.0098)	0.789***	(0.0228)	0.187***	(0.0244)	1.91	3	0.59
14	153	0.012	(0.0775)	0.667***	(0.0810)	0.33***	(0.0440)	4.7	4	0.32
15	167	-0.040	(0.0300)	0.807***	(0.0458)	0.133***	(0.0223)	1.44	6	0.96
16	822	0.060***	(0.0095)	0.735***	(0.0307)	0.074***	(0.0144)	9.61	6	0.14
17	1,080	0.038***	(0.0060)	0.717***	(0.0182)	0.205***	(0.0098)	5.76	4	0.22
18	482	-0.022	(0.0190)	0.884***	(0.0300)	0.097***	(0.0109)	4.56	4	0.34
20	2321	0.046***	(0.0100)	0.715***	(0.0242)	0.182***	(0.0114)	7.52	4	0.11
21	496	0.027	(0.0343)	1.023***	(0.0567)	0.050	(0.0327)	7.28	9	0.61
22	2,424	0.019**	(0.0074)	0.788***	(0.0183)	0.117***	(0.0144)	10.08**	4	0.04
23	1,981	0.033***	(0.0065)	0.780***	(0.0225)	0.162***	(0.0205)	2.55	4	0.64
24	1,787	0.028***	(0.0062)	0.881***	(0.0291)	0.136***	(0.0105)	12.52**	4	0.01
25	4,376	0.014***	(0.0033)	0.833***	(0.0117)	0.087***	(0.0078)	18.86***	4	0.00
26	1,639	0.003	(0.0117)	0.808***	(0.0223)	0.199***	(0.0148)	7.11*	3	0.07
27	2,331	0.040***	(0.0035)	0.817***	(0.0231)	0.118***	(0.0102)	3.9	4	0.42
28	6,194	0.044***	(0.0044)	0.938***	(0.0117)	0.077***	(0.0046)	41.95***	4	0.00
29	1,937	0.032***	(0.0053)	0.710***	(0.0357)	0.093***	(0.0122)	6.19	4	0.19
30	607	0.013	(0.0153)	0.885***	(0.0265)	0.134***	(0.0077)	4.14	4	0.39
31	756	0.024**	(0.0078)	0.851***	(0.0207)	0.111***	(0.0126)	1.09	4	0.90
32	771	0.018*	(0.0090)	0.810***	(0.0318)	0.149***	(0.0175)	6.93	4	0.14
33	972	0.049*	(0.0197)	0.978***	(0.0236)	0.06***	(0.0096)	1.68	4	0.79

Source: *cost structure survey*; *** p<0.01, ** p<0.05, * p<0.1; Standard errors in parentheses

Table D-10: Average TFP under the assumption $d = 0.5$ and $d = 1.5$

Ind. Code	N	Mean TFP (not contr. for T)	Mean TFP (contr. for T)	Diff.	Std.Err. of Diff.	t-value	p-value	df_t	Diff
TFP under the assumption of $d = 0.5$									
10t33	35,909	9.873	9.975	-0.102	0.001	-70.56	0.00	71,761.4	1.04%
13	698	8.839	8.952	-0.112	0.007	-15.51	0.00	1,393.9	1.27%
16	822	10.646	10.894	-0.248	0.014	-17.11	0.00	1,637.7	2.33%
17	1,080	8.806	8.903	-0.098	0.006	-15.09	0.00	2,150.0	1.11%
20	2,321	9.577	9.508	0.069	0.007	10.46	0.00	4,632.2	-0.72%
22	2,424	9.758	9.966	-0.209	0.006	-37.33	0.00	4,788.7	2.14%
23	1,981	9.240	9.346	-0.106	0.007	-16.03	0.00	3,956.2	1.14%
24	1,787	9.213	9.335	-0.122	0.007	-17.16	0.00	3,566.4	1.32%
25	4,376	10.157	10.302	-0.145	0.005	-31.65	0.00	8,703.5	1.43%
27	2,331	9.452	9.934	-0.482	0.005	-106.60	0.00	4,405.2	5.10%
28	6,194	9.959	10.085	-0.126	0.003	-42.75	0.00	12,378.6	1.26%
29	1,937	10.649	10.846	-0.197	0.011	-18.51	0.00	3,861.0	1.85%
31	756	9.779	9.821	-0.041	0.007	-5.85	0.00	1,508.8	0.42%
32	771	9.460	9.571	-0.112	0.011	-10.17	0.00	1,539.2	1.18%
33	972	9.864	10.079	-0.215	0.008	-28.33	0.00	1,938.0	2.18%
TFP under the assumption of $d = 1.5$									
10t33	35,909	9.872	9.975	-0.103	0.001	-70.74	0.00	71,760.9	1.04%
13	698	8.839	8.954	-0.115	0.007	-15.81	0.00	1,393.9	1.30%
16	822	10.645	10.895	-0.250	0.014	-17.24	0.00	1,637.6	2.35%
17	1,080	8.806	8.903	-0.097	0.006	-15.00	0.00	2,150.0	1.10%
20	2,321	9.577	9.508	0.069	0.007	10.44	0.00	4,632.1	-0.72%
22	2,424	9.759	9.968	-0.208	0.006	-37.25	0.00	4,788.8	2.13%
23	1,981	9.239	9.346	-0.106	0.007	-16.14	0.00	3,956.1	1.15%
24	1,787	9.212	9.335	-0.123	0.007	-17.35	0.00	3,566.4	1.34%
25	4,376	10.157	10.302	-0.145	0.005	-31.64	0.00	8,703.5	1.43%
27	2,331	9.453	9.934	-0.482	0.005	-106.55	0.00	4,405.5	5.09%
28	6,194	9.959	10.084	-0.126	0.003	-42.79	0.00	12,378.6	1.26%
29	1,937	10.649	10.847	-0.198	0.011	-18.51	0.00	3,860.9	1.85%
31	756	9.780	9.818	-0.039	0.007	-5.46	0.00	1,508.8	0.39%
32	771	9.460	9.571	-0.112	0.011	-10.19	0.00	1,539.2	1.18%
33	972	9.864	10.078	-0.214	0.008	-28.21	0.00	1,938.0	2.17%

Source: *cost structure survey*; own calculations

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