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# When structural reforms of labor markets harm productivity. Evidence from the German IAB panel

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We find firm-level evidence that removing labor market rigidities can harm productivity growth. This holds, in particular, in industries with a high 'cumulativeness' of knowledge, i.e., when accumulation of worker-embodied (and often 'tacit') knowledge from experience is important for innovative competencies. We conclude that there is a trade-off between the efficient allocation of scarce resources in a static neoclassical perspective and dynamic Schumpeterian efficiency, the latter requiring rigidities in labor markets that are valuable for innovation.

**JEL classification:** D24, E24, J01, J08, J21, J41, O31, O32

> "Perfect competition … is a condition for optimal allocation of resources … But …introduction of new methods of production and new commodities is hardly conceivable with perfect … competition … And this means that the bulk of … economic progress is incompatible with it. As a matter of fact, perfect competition is and always has been temporarily suspended whenever anything new is being introduced …"
>
> Joseph A. Schumpeter (1942): *Capitalism, Socialism and Democracy*, New York: Harper, p. 104–105.

## 1. Introduction

From the 1970s and 1980s onwards, a growing community of supply-side economists emphasized that European unemployment was high due to rigid labor markets. In a supply-side view, the most important labor market rigidities related to firing restrictions, downwardly rigid wages, too generous social benefits, or centralized bargaining (e.g., Canto *et al.*, 1983). The supply-side revolution also replaced the Keynesian target of full employment by the concept of (higher) 'natural' or NAIRU unemployment rates. The latter rates should be high enough to keep the labor force disciplined and prevent inflation-enhancing wage growth (Shapiro and Stiglitz, 1984).

In this paper, we argue that supply-side reforms may indeed enhance the efficient use of scarce resources in a static neoclassical framework, but they are harmful to innovation and the speed of diffusion of innovations. In other words, reforms that enhance static Walrasian efficiency can harm Schumpeterian dynamic efficiency, which will ultimately result in lower productivity gains. In recent years, various studies addressed a persistent productivity growth slowdown in major OECD countries (Cardarelli and Lusinyan, 2015; OECD, 2015; Bailey and Montalbano, 2016). Such studies ignored, however, the hypothesis that the observed slowdown might have something to do with supply-side labor market reforms.

Why should removing rigidities in the functioning of labor markets be harmful to innovation? Recent neo-Schumpeterian literature offers several arguments. Among the most important arguments are:

First, supply-side reforms change power relations between capital and labor, leading to weaker wage growth which in turn reduces productivity growth through a slower speed of diffusion of labor-saving technology (Vergeer and Kleinknecht, 2011, 2014).

A second group of arguments relates to easier firing and a larger labor turnover creating unfavorable conditions for firm-sponsored training (Belot *et al.*, 2002) or for the management of firm-specific knowledge, especially if such knowledge is 'tacit' and embodied in people (Polanyi, 1966; Lorenz, 1999). Shorter job tenures can also weaken the historical memories of firms, turning them into *un*learning organizations that repeat past mistakes. Shorter job tenures can also reduce gains from learning-by-doing; or they can diminish the loyalty and commitment of personnel. The latter can ease the leaking of precious knowledge and trade secrets to competitors, thus increasing Pigouvian externalities that discourage investments in new knowledge. It comes as no surprise that the rise of flexible labor correlates with the growth of management bureaucracies for monitoring and control (Kleinknecht *et al.*, 2016). Thicker management layers can threaten the professional autonomy of creative people, besides driving up overhead costs.

Another argument (to be empirically tested in this paper) relates to a distinction between industries with a high or low "cumulativeness of knowledge," building on work by Peneder (2010). Firms in industries with a low cumulativeness of knowledge rely primarily on acquisition of general knowledge from external sources. Highly cumulative innovators rely more on internal sources, having a strong focus on the accumulation of firm-specific knowledge from experience acquired in a process of continuous improvement of products, processes, or systems. Such knowledge tends to be 'tacit' (Polanyi, 1966), i.e., it is poorly documented and mainly embodied by people. This makes longer job tenures in well-protected insider positions attractive to employers.

The most important counter-arguments by supply-side economists can be summarized as follows: First, if the labor market has firing rigidities, reallocation of the labor force from old and declining sectors to new and dynamic sectors is slowed down (Bartelsman *et al.*, 2016). Second, labor-saving innovations can be frustrated if people that are made redundant cannot be quitted easily (Martin and Scarpetta, 2012). Third, well-protected and powerful insiders could ask for higher wages that would capture (part of) a firm's monopoly rents from innovation, thus reducing the incentive to accept innovative risks. Forth, following job matching theory (Pissarides, 2000), rigid firing reduces numbers of job matches and thus reduces the probability of employees finding a job match where they can be more productive. Fifth, according to efficiency wage theory, the threat of easy firing is supposed to increase productivity as it may prevent 'shirking' (Sjostrom, 1993; Scoppa, 2010).

Rather than further elaborating on the merits of arguments and counter-arguments (see the survey by Kleinknecht, 2020), this paper will provide an empirical analysis, exploiting the experience of labor market reforms in Germany between 2002 and 2005, the so-called Hartz reforms The most important parts of the German Hartz reform package enhanced manpower agency work and self-employment, but the most controversial part related to a substantial sobering of unemployment benefits. Sobering meant lower amounts and shorter durations of benefits, as well as stricter conditions for access to benefits. In subsequent years, flexible arrangements or 'atypical' work were rising in Germany (Tangian, 2011; Schulze Buschoff, 2014). But the Hartz reforms were also praised for having reduced unemployment (e.g., Gaskarth, 2014). Moreover, several studies also found a substantially negative influence of the reforms on wages and on the quality of jobs, especially for people who returned to the labor market after spells of unemployment (e.g., Arent and Nagl, 2013; Engbom *et al.*, 2015; Giannelli *et al.*, 2016). All this contributed to a substantial rise in income inequality, German Gini coefficients rising from 26.2 in year 2000 to 29.2 in 2008 (OECD, 2020).

The paper is organized as follows. Section 2 discusses previous research on a possibly negative influence of labor market deregulation on innovation or productivity, emphasizing that such research missed an important control variable: control for the type of innovation model that is dominant in an industry. This omitted variable problem may explain why a few studies found no (or only small) negative effects of more flexible labor on innovation or productivity. Section 3 introduces our database and estimation strategy. Section 4 documents results, followed by conclusions in Section 5.

## 2. Recent empirical research

Empirical studies of the impact of labor market reforms on innovation and productivity growth are diverse in terms of sampling, the period of study or levels of aggregation. With respect to flexibility of labor, studies differ in terms of utilizing numerical (other than functional) flexibility or wage flexibility. Many studies find *negative* relationships between, on the one hand, different measures of contractual flexibility of labor, and, on the other hand, indicators of innovation or productivity. Let us give some examples from the quickly growing literature.

Vergeer and Kleinknecht (2011) and Vergeer and Kleinknecht (2014) ran cross-country regressions on 19 OECD countries from 1960 to 2004, showing that wage-cost saving flexibilization of labor markets has a negative impact on labor productivity growth. A one percentage point change in growth rates of real wages leads to a medium-term change in labor productivity growth by 0.31–0.49 percentage points, depending on the model specification. Lisi (2013) used industry-level panel data to evaluate the impact of employment protection legislation (EPL) for temporary and permanent employment in EU countries. The main finding is that the use of temporary contracts has a negative, even if small in magnitude, effect on labor productivity.

Pariboni and Tridico (2020) sampled industry-level data from 25 European countries for the period 1995–2016 and found a negative relationship between labor productivity growth and temporary employment. Damiani and Pompei (2006) use industry-level data (1995–2005) of 16 European countries in their analysis of the impact of flexible employment on multi-factor productivity. They find a negative relationship between flexible labor and multi-factor productivity and argue that shorter-term contracts discourage investment in skills, notably in labor-intensive services.

In a firm-level study, Lucidi and Kleinknecht (2010) report a negative relationship between, on the one hand, the utilization of fixed term contracts and the relative price of capital versus labor, and, on the other hand, labor productivity growth in Italy. In the Netherlands, Kleinknecht *et al.* (2014) find that high shares of temporary workers have a negative impact on the probability that a firm will invest in R&D, this relationship being strongest in sectors with a 'routinized' innovation regime. The latter result is confirmed in similar estimates on a different database by Wachsen and Blind (2016).

In their Probit analysis of firm-level data, Hoxha and Kleinknecht (2020) conclude that high (external and numerical) labor flexibility is negatively related to the probability of performing R&D and/or to introduce innovations. Using German establishment data from the *Institut für Arbeitsmarkt- und Berufsforschung* (*IAB*), they find that, in industries classified by Peneder (2010) as "medium and highly cumulative", flexible labor has a negative impact on the probability to innovate, while in sectors with "low cumulativeness", coefficients are lower and often turn out insignificant.

The present paper comes close to the papers by Hirsch and Mueller (2012) and Lisi and Malo (2017) but it goes one step further in using Peneder's (2010) classification of industries by degree of cumulativeness of knowledge. Hirsch and Mueller (2012) investigate the effect of temporary agency work on a firm's productivity using IAB data between 2003 and 2010. They hypothesize that the use of temporary work for enhancing numerical flexibility and screening job candidates may increase productivity, whereas temporary workers' lower firm-specific human capital as well as spillover effects on the firm's permanent employees may adversely affect productivity.

When examining the reasons why firms engage in temporary contracts, Hirsch and Mueller (2012) argue that this is an attempt by firms to meet flexibility requirements within a two-tier labor market characterized by strong dismissal protection and market restraints on other types of flexible labor. In the IAB survey, however, firms reported 'seasonal peaks in demand' and 'fast availability of new personnel' as the two highest ranking motives (39% and 40%) for their use of temporary contracts; respondents give lower importance to factors such as uncertainty about economic prospects, screening before offering permanent jobs, savings on employment recruitment and termination costs, or matching very specific job requirements. This order of reasons for choosing flexible labor sheds some doubt on the argument by Pissarides (2000) that firms use temporary contracts mainly for better screening new employees and thus create more successful matches.

Lisi and Malo (2017) also study the impact of temporary employment on productivity growth, using an industry-level panel of European countries. They find a negative effect of temporary employment on productivity growth and this effect is larger in skilled sectors. An increase of 10 percentage points of the share of temporary employment in skilled sectors reduces labor productivity growth by about 1–1.5 percentage points and in unskilled sectors this estimate is between 0.5 and 0.8 percentage points.

There are a few studies, however, that find either insignificant (Arvanitis, 2005) or even positive effects. For example, Bjuggren (2018) finds a positive productivity effect of a partial labor market reform in Sweden, when employers were allowed to abandon the 'last-in, first-out' principle for firing personnel. Another example is Fedotenkov *et al.* (2022) who conclude that, during the Great Recession after the Lehman Crash of 2008, easier firing *enhances* labor productivity growth. They emphasize, however, that this effect only holds during the Great Recession, while long-run effects may differ. In the following, we argue that ambiguous results in previous studies may, among others, have to do with an omitted variable problem: lack of control for the innovation regime that is dominant in a sector.

Three earlier studies made a distinction between a Schumpeter-I and a Schumpeter-II innovation regime, finding a negative impact of flexible labor on innovation (Kleinknecht *et al.*, 2014; Wachsen and Blind, 2016) and on labor productivity (Vergeer *et al.*, 2015). This negative impact is highly significant in a Schumpeter-II regime, and less so in a Schumpeter-I regime. But the three studies still relied on a rather crude distinction between the two innovation regimes. Peneder (2010) provided an improved definition of innovation regimes, measuring the degree to which the innovative process mainly depends on internal or on external sources of knowledge. A stronger dependence on internal knowledge sources hints to the importance of firm-specific knowledge acquired through experience with past technological projects. Such knowledge tends to be weakly documented and "tacit," i.e., it is often embodied by people. Firms relying more on low-cumulative knowledge rely primarily on *external* sources of knowledge. The latter knowledge is somehow standardized and codified and hence tradable on knowledge markets.

In the relationship between flexibility and productivity growth, this distinction is relevant. High shares of temporary workers and a higher job turnover lead to a higher inflow of "fresh blood," i.e., people with new ideas and networks. This might favor innovation and productivity growth if firms rely on readily available external and general knowledge in garage business firms or in traditional industries with a mature and highly standardized technology that can be acquired on external markets. In innovative sectors with a high cumulativeness of knowledge, however, flexibility may be counterproductive. In these sectors, longer job tenures increase commitment and loyalty which, in turn, makes the management of knowledge, mobilization of (tacit) knowledge from the shop floor and knowledge accumulation easier (Lorenz, 1999; Hoxha and Kleinknecht, 2020).

The taxonomy by Peneder assesses the 'cumulativeness of knowledge' by counting numbers of sources of innovative ideas considered by firms to have been important for their innovations. Data on cumulativeness are derived from various vintages of the *Community Innovation Survey* (*CIS*), covering a larger number of countries. Peneder (2010) shows that within the manufacturing sector, industries with a 'high cumulativeness' of knowledge correlate with industries that have a high innovation and R&D capacity. In service sectors this correlation is weaker (Peneder, 2010, Table 5). Peneder's index structures knowledge cumulativeness by industry from a low to a high cumulativeness of knowledge (see Appendix II for a listing of industries). Two papers that recently explored the relevance of the Peneder index in the relationship between temporary employment and innovation are by Hoxha and Kleinknecht

(2020), using German firm-level data and by Cetrulo *et al.* (2019), using European sector-level data. Both papers find a negative correlation between temporary employment and innovation that turns out to be stronger in sectors where cumulativeness is high. In the following, we examine whether this also holds for labor productivity growth, using firm-level panel data for Germany.

## 3. Data and methodology

In our test of the relationship between flexibility in labor relations and productivity growth in German establishments we use both a between and a within estimation method. As already mentioned, we make a distinction of industries by degree of "cumulativeness of knowledge", i.e., the degree to which the innovative process relies on internally accumulated or on externally acquired knowledge. We estimate separate equations for industries with a low versus a medium and high cumulativeness of knowledge as detailed in Appendix II. We hypothesize that flexible labor harms productivity growth more in sectors that have a medium or high degree of knowledge cumulativeness.

Our data are from the Institute for Employment Research in Germany (IAB). The IAB Establishment Panel is a representative survey of employment parameters at individual German establishments. It is a balanced panel in which all firms can be observed during all years of our observation period. Around 16 000 establishments from all sectors of the economy and of all sizes are surveyed annually and nationwide. The field work is done from the end of June until October. Data are made available to researchers via remote access or on-site at the Federal Employment Agency's Research Data Centre at IAB. We confine our analysis to manufacturing and commercial service firms, omitting non-commercial and governmental organizations.

The nationally representative IAB survey covers a wide range of questions related to an establishment's personnel policy. The establishment panel exists since 1993 in West Germany and since 1996 it also covers firms from East Germany. The data reports information on firm performance and human resource strategies during the previous year or during the first half of the current year of study. The surveys are conducted orally, with trained interviewers visiting the firm. The latter implies that data quality is high. Actually, we did not feel a need to omit outliers.

We use data from 1998 onwards (when innovation indicators have been included for the first time) and end in 2016. Descriptive statistics on key variables can be found in Appendix I. We rely on two indicators of flexibility of labor. First, percentages of temporary workers and, second, percentages of contracts that were terminated during the first half of the business year. The first indicator is a direct measure of flexible labor, but is more limited as it covers only one form of flexibility. On average over time, only around 5% of total personnel in the sample is temporary, implying that the indicator has limited variation. The second indicator does not directly measure contractual flexibility. It gives, however, a more comprehensive picture of a firm's choice of permanent versus (various types of) flexible contracts, which influences its ability for quitting people under adverse circumstances.

In order to empirically test possible non-linearities, we augment our main model with the squares of our flexibility variables. Controls include time-variant variables such as:

- the lag of the log productivity, in order to control for the persistency of the dependent variable and test the possibility that firms that exhibit high productivity levels have lower productivity growth;
- firm size (i.e., persons employed), as larger firms can exploit economies of scale, and thus have higher productivity growth;
- a Likert scale measure of the degree by which firms have modernized their equipment, which is a proxy for rejuvenation of a firm's capital stock;
- firm age and age squared, as older firms are expected to be more productive, but this effect may diminish with age (Huergo and Jaumandreu, 2004);
- following Hirsch and Mueller (2012) we include percentages of manpower agency workers and percentages of freelancers, as well as their respective squares;

- percentages of part-time workers, as literature on this is divided. Künn-Nelen *et al.* (2013) find a positive effect of part-time work on productivity, but Garnero *et al.* (2014) find the opposite.

Finally, we include time-invariant variables such as a dummy for whether the firm is independent (i.e., not part of a conglomerate) and a dummy for whether the firm has a works council, the latter indicating a cooperative 'Rhineland' type (as opposed to an Anglo-Saxon) management culture.

As to our indicators of flexibility, one should note that there is a hierarchy in the 'fluidness' of labor. Under adverse shocks, manpower agency workers can be most quickly quitted, usually within a few hours or days. Temporary workers or freelancers can also be easily quitted, but a bit less quickly if they have a contract for a certain period (or for a certain project). They automatically leave the firm after expiration of their contract, which may take weeks or months. Our indicator of percentages of contracts terminated during the first half of the year is the least fluid indicator, as it also covers people on permanent contracts.

The latter is relevant as work by Fedotenkov *et al.* (2022) reminds us that our flexibility indicators may be biased against our hypothesis if adverse shocks occur to individual firms or economy-wide. Note that labor productivity is defined as gross domestic product (GDP) divided by labor input. Under a negative shock and easy firing, labor input can be quickly reduced. Hence, the ratio of GDP/labor will look more favorably than in labor markets with firing restrictions. Firing restrictions would typically encourage some labor hoarding and therefore the ratio of GDP/labor appears to be lower. This is the reason why Fedotenkov *et al.* (2022) find a *positive* impact on labor productivity of easy-firing regimes during the Great Recession after the Lehman Crash. We should be aware, however, that a favorable ratio of GDP/labor does not need to indicate a higher speed of technical change. It can rather be a short-run bookkeeping effect. And, this effect may be largest among those flexible workers that can be most quickly fired, i.e., manpower agency workers. The bias may also hold for temporary workers and freelancers, but a bit less so.

As dependent variable, the difference of the log of value added per working hour is used (for simplicity called: '$y$'). The difference of the log is approximately the ratio of change over the previous value, henceforth the growth of productivity variable. The following model will be estimated:

$$d.\log\left(y_{i,t}\right) = Flex'_{i,t}\beta_i + \log\left(y\right)_{i,t-1}\gamma + X'_{i,t}\alpha +_t + \varphi_i + \varepsilon_{i,t}.$$

The variables of interest are temporary contracts and contracts terminated during the first half year, and their respective squares. As a robustness check, we run four different types of estimates: pooled Ordinary Least Squares (OLS) (Table 1), random effects (Table A.2.), fixed effects (Table 2) and system Generalized Method of Moments (GMM) (Table 3). There are benefits to this order of estimation. First, for one to choose between difference and system GMM, one needs to perform both the pooled OLS estimate and the fixed effect estimate. The former estimate for the autoregressive part (pooled OLS) can be considered an upper-bound estimate, while the corresponding fixed-effects estimate is a lower bound estimate. The choice to perform the random effect estimator (Appendix, Table A.2.) is to report the between estimator as failing to include random slopes that can generate anti-conservative standard errors, and if random intercepts are not normally distributed, this introduces biases, however small they are (Bell *et al.*, 2019; see also the note on GMM in the Appendix).

The GMM-SYS estimator (see Annex III for more details) eliminates the fixed effects by combining two equations in one system. The first equation is expressed in levels with their first differences as instruments, and the second equation is expressed in first differences with levels as instruments. The starting point would be the initial transform model expressed in first differences:

$$d2.\log\left(y_{i,t}\right) = d.Flex'_{i,t}\beta_i + d.\log\left(y\right)_{i,t-1}\gamma + d.X'_{i,t}\alpha + d._t + d.\varepsilon_{i,t}$$

## 4. Results

In Tables 1–3, the first column shows results for the total sample without distinction by knowledge cumulativeness; the second column shows the output for firms that are part of the *low* cumulativeness group of industries for which we expect flexibility to have a weak or no effect on productivity. The third column covers the estimates for firms in the medium plus high knowledge cumulativeness industries for which we expect negative effects of flexibility on productivity.

Table 1 shows the estimates for the pooled OLS. A 1% higher productivity *level* last year corresponds to an 0.24% lower productivity *growth* this year, holding all else equal. This coefficient holds independently of the degree of cumulativeness of knowledge. Moreover, the flexibility variables underline the above-mentioned bias problem: The most 'fluid' type of work, i.e., manpower agency workers turns out *positive*, implying that firms that have higher shares of very easy-to-fire people show higher productivity growth. The same holds for freelance workers. But despite the named bias, the coefficient for temporary workers is negative, although with a small coefficient.

Our most comprehensive indicator (people leaving the firm during the first half year) is significant and shows the hypothesized negative relationship within the total sample, and more so, for the industries with a medium and high degree of cumulativeness of knowledge. For every percentage point increase in the share of terminated contracts, productivity growth decreases by approximately 0.6% for the full sample and by 0.8% among the highly cumulative industries. Again, as expected, coefficients in the low cumulativeness industries are insignificant. The squared element is significant and positive in the entire sample and in the highly cumulative industries.

Lastly, percentages of part-timers have a negative effect on productivity growth and there is an inverse U-shaped relationship between firm age and productivity growth, the latter maximizing at an age of 25 years.

Moving forward to the fixed effects in Table 2, the estimate for the lag of productivity levels decreases and becomes even negative in a range of −0.79% to −0.76%. This confirms the tests by Roodman (2009) and Arellano and Bond (1991) which state that with respect to the autoregressive element in the model, the pooled OLS estimate should serve as an upper bound and the

**Table 1.** Pooled OLS estimates (*t*-values in brackets)

| Variables | (Full sample) $d.\log(y)_t$ | (Low cumulative) $d.\log(y)_t$ | (High cumulative) $d.\log(y)_t$ |
|---|---|---|---|
| $\log(y)_{t-1}$ | −0.24*** (−48.91) | −0.24*** (−36.62) | −0.24*** (−34.80) |
| % temporary | −0.012** (−2.16) | −0.007 (−0.88) | −0.02** (−2.47) |
| % temporary-sq | −0.006 (−0.78) | −0.006 (−0.51) | −0.0011 (−0.35) |
| % terminated | −0.006*** (−2.81) | −0.005 (−1.14) | −0.0081*** (−2.80) |
| % terminated-sq | 0.0093*** (2.68) | 0.0016 (0.95) | 0.0009*** (3.04) |
| State of technical equipment | 0.005*** (13.40) | 0.005*** (9.66) | 0.0045*** (9.14) |
| Log (firm size) | 0.027*** (47.45) | 0.028*** (34.77) | 0.027*** (32.30) |
| Works council | 0.004*** (4.84) | 0.0034*** (2.88) | 0.0046*** (3.94) |
| Independent firm | −0.0041*** (−5.22) | −0.006*** (−5.34) | −0.0019* (−1.76) |
| % of agency | 0.045*** (5.88) | 0.021* (1.91) | 0.061*** (5.64) |
| % of agency-sq | −0.05*** (−3.83) | −0.010 (−0.46) | −0.07*** (−4.30) |
| % of freelance | 0.043*** (5.25) | 0.045*** (2.95) | 0.043*** (4.47) |
| % of freelance-sq | −0.03*** (−2.40) | −0.039* (−1.70) | −0.027* (−1.83) |
| % of part-timers | −0.024*** (−18.93) | −0.023*** (−13.23) | −0.025*** (−14.36) |
| Age | −0.0008*** (−4.29) | −0.000*** (−2.53) | −0.0009*** (−3.79) |
| Age-Sq | 0.00002*** (3.11) | 0.000* (1.67) | 0.00002*** (2.97) |
| Year-Dummies | Yes | Yes | Yes |
| Observations | 36 268 | 19 041 | 17 227 |
| Establishments | – | – | – |
| *R*-squared | 15.87% | 15.03% | 17.25% |
| *F* | 98.84 | 50.34 | 46.14 |

*** = significant at 99% level;
** = significant at 95% level;
* = significant at 90% level.

**Table 2.** Fixed effects estimates (*t*-values in brackets)

| Variables | (Full sample) $d.\log(y)_t$ | (Low cumulative) $d.\log(y)_t$ | (High cumulative) $d.\log(y)_t$ |
|---|---|---|---|
| $\log(y)_{t-1}$ | −0.76*** (−70.41) | −0.79*** (−51.71) | −0.77*** (−50.94) |
| % temporary | −0.018** (−2.13) | −0.013 (−1.06) | −0.025** (−2.09) |
| % temporary-sq | 0.006 (0.50) | −0.002 (−0.15) | 0.014 (0.88) |
| % terminated | 0.015*** (6.84) | 0.013*** (2.84) | 0.015*** (5.03) |
| % terminated-sq | −0.003*** (−2.26) | 0.002 (0.14) | −0.004*** (−2.17) |
| State of technical equipment | 0.0032*** (5.85) | 0.0026*** (3.28) | 0.0039*** (5.16) |
| Log (firm size) | 0.049*** (29.49) | 0.048*** (17.80) | 0.050*** (22.72) |
| Works council | 0.0060*** (2.43) | 0.011*** (2.79) | 0.0028 (0.83) |
| Independent firm | −0.00011 (−0.11) | 0.0005 (0.23) | −0.0010 (−0.57) |
| % of agency | 0.032*** (2.83) | 0.030* (1.68) | 0.030** (2.07) |
| % of agency-sq | −0.17 (−1.07) | −0.001 (−0.03) | −0.022 (−1.17) |
| % of freelance | −0.0212 (−1.75) | −0.043** (−1.99) | 0.0006 (0.05) |
| % of freelance-sq | 0.0214 (1.3) | 0.045 1.36 | 0.002 (0.11) |
| % of part-timers | −0.019*** (−7.13) | −0.019 (−4.57) | −0.023*** (−5.37) |
| Age | 0.0005* (1.65) | 0.0007 (1.53) | 0.0006 (1.29) |
| Age-Sq | −0.0002* (−1.83) | −0.00002 (−1.40) | −0.0000 (−1.51) |
| Year-Dummies | Yes | Yes | Yes |
| Observations | 36 268 | 19 041 | 17 227 |
| Establishments | 10 552 | 5644 | 5443 |
| *R*-squared | 42% | 43% | 43% |
| *F* | 196 | 108.53 | 120.04 |

*** = significant at 99% level;
** = significant at 95% level;
* = significant at 90% level.

**Table 3.** GMM-SYS estimates (*t*-values in brackets)

| Variables | (Full sample) $d.\log(y)_t$ | (Low cCumulative) $d.\log(y)_t$ | (High cumulative) $d.\log(y)_t$ |
|---|---|---|---|
| $\log(y)_{t-1}$ | −0.42*** (−16.75) | −0.39*** (−12.60) | −0.38*** (−11.42) |
| % temporary | 0.02 (0.58) | 0.005 (0.13) | 0.018 (0.45) |
| % temporary-sq | −0.01 (−0.18) | −0.017 (−0.28) | −0.017 (−0.26) |
| % terminated | −0.049*** (−2.72) | 0.001 (−0.03) | −0.072*** (−2.16) |
| % terminated-sq | 0.015 (0.86) | −0.0103 (−0.47) | 0.013** (0.76) |
| State of technical Equipment | 0.0026 (1.51) | 0.0038* (1.94) | 0.0044*** (2.01) |
| Log (firm size) | 0.0431*** (15.79) | 0.040*** (11.32) | 0.039*** (11.10) |
| Work council | −0.0025 (−0.77) | −0.006 (−1.43) | 0.0030 (0.72) |
| Independent | −0.013*** (−4.14) | −0.020*** (−4.80) | −0.0032 (−0.78) |
| % of agency | 0.02*** (2.13) | 0.019*** (2.97) | 0.023*** (3.43) |
| % of agency-sq | 0.010 (0.11) | 0.025 (1.79) | −0.018 (−1.36) |
| % of freelance | 0.057 (0.92) | 0.084 (0.88) | 0.098 (1.64) |
| % of freelance-sq | 0.085 (0.75) | 0.037 (0.25) | −0.002 (−0.02) |
| % of part-timers | −0.024*** (−10.13) | −0.02*** (−8.02) | −0.025*** (−6.59) |
| Age | −0.001 (−1.61) | −0.0010 (−1.33) | −0.0013 (−1.54) |
| Age-Sq | −0.00006 (−0.16) | 0.000048 (0.14) | 0.0000 (0.60) |
| Year-Dummies | Yes | Yes | Yes |
| Observations | 22 317 | 12 151 | 10 166 |
| Instruments | 165 | 165 | 165 |
| *F* | 13.09 | 6.93 | 8.12 |
| Arellano Bond (AR 2) | 0.001 | 0.001 | 0.08 |
| Hansen *P*-value | 0.35 | 0.002 | 0.413 |

*** = significant at 99% level;
** = significant at 95% level;
* = significant at 90% level.

fixed effect estimate should serve as a lower bound. Our estimate of interest is that of percentages of temporary workers which is again negative and significant for the entire sample and for the highly cumulative industries. For the latter group, this estimate shows a slight increase in magnitude when compared to the pooled OLS, from 2% to 2.5%, meaning that a one percent increase of temporary workers would cause a 2.5% decrease in productivity growth. The linear estimate for the percentage of terminated contracts turns positive and the overall marginal effect exhibits an inverse U-shaped relationship with a productivity maximizing percentage of terminated contracts of around 2.5% for the entire sample and 1.9% for the highly cumulative firms This means that if firms fire more than 2.5% of their personnel the effect on productivity growth will be negative.

All control variables behave according to what is theoretically expected. Only the effect of works councils on productivity growth becomes insignificant in the highly cumulative industries and firm age loses its significance when controlling for knowledge cumulativeness.

Table 3 covers results from GMM-SYS. To increase instrument validity, in the instrument bucket, besides the differences of the above-mentioned independent variables, the log of investment and a variable that measures whether the firm has gone through major restructuring in the last six months are added as exogenous variables. The latter two variables were not included in the OLS and Fixed Effects (FE) estimates. The Hansen test indicates that the instruments are valid only for the full sample and for the highly cumulative industries. Hence the outcomes for low-cumulative industries should be interpreted with caution.

Besides the instrument set being essentially the same throughout all three models in Table 3, the Arellano–Bond tests for autocorrelation indicate that only the model for the subsample of highly cumulative industries does not suffer from autocorrelation. Our instrument set includes the lags of our covariate and two exogenous variables, namely the log of investment and whether the firm had a major restructuring operation in the past six months. The (insignificant) year dummies are excluded from our instrument set. The *P*-values for the Hansen test of overidentification restrictions indicate that the instruments are valid only for the full sample and for highly cumulative industries.

From the GMM-SYS estimate, it is reassuring that the lag of productivity is again significant and negative and remains in between the range of the estimate derived from the pooled OLS and the fixed effects model. Other than in the pooled OLS and in the fixed effects model, however, temporary contracts still have the expected sign, but become insignificant in both the linear and quadratic part. This may have to do with the above-mentioned bias problem. Our more comprehensive measure of firing flexibility (i.e., percentages of contracts terminated during the first half year) remains significant and negative in its linear component but turns insignificant in its quadratic part. We conclude that a high firing flexibility has a (linear) negative impact on productivity growth.

Holding all else equal, increasing firing flexibility (i.e., shares of terminated contracts) with one percentage point decreases productivity growth by approximately 5% for the full sample and 7.2% for highly cumulative industries. As compared to the previous OLS and FE estimates, however, some coefficients lose significance. For example, modernization of equipment is still significant in highly cumulative industries, but not for the total sample, and works councils become insignificant throughout. The same holds for the age variable that becomes insignificant throughout. With respect to these three variables, we should therefore be cautious in our interpretation of the above OLS and FE estimates.

On the other hand, our controls behave as expected. In all model specifications, firms with high *levels* of productivity exhibit lower productivity *growth*. In other words, the closer you are to the best-practice frontier, the harder it becomes moving forward. Moreover, independent firms tend to have lower productivity gains than firms that are part of a conglomerate. The same holds for firms with high shares of part-time workers: the latter contribute negatively to productivity growth.

## 5. Conclusions and discussion

We explored the firm-level relationship between flexibility of labor and productivity growth in a dynamic panel of German establishments. Following all three models estimated (i.e., OLS, FE, and GMM-SYS), we find support for the hypothesis that there is a *negative* relationship between a firm's flexibility to fire personnel and its productivity performance. Other than in the above OLS and FE estimates, however, the estimates for percentages of temporary contracts turn out insignificant in our preferred GMM-SYS estimates. This may be ascribed to a bias against our hypothesis: Compared to workers on permanent jobs, temporary workers are easier to fire. Hence, under adverse shocks, a firm will quit them with priority, and this can, in the short-run, make the productivity figures (GDP/Labor) look more favorable in firms that have high rates of workers that are easy to fire. In this case, a higher GDP/Labor ratio does not need to indicate a higher speed of technical change. It is rather a short-run bookkeeping effect due to a quick reduction of labor input.

Compared to previous studies, a new insight comes from the "cumulativeness of knowledge" variable. We find that the harmful impact of flexible personnel policies on productivity growth differs, depending on different degrees of cumulativeness of the knowledge that is required for innovation. As expected, our negative coefficients are larger in industries with a medium or high cumulativeness according to Peneder (2010). This implies that higher shares of flexible personnel are more counterproductive for firms that heavily depend on the accumulation of knowledge from experience that, due to its "tacitness", tends to be weakly documented and is mainly embodied in workers. Some ambiguities of results in earlier studies are likely to come from not taking account of knowledge cumulativeness. Among the authors that have (in one way or the other) considered knowledge regimes, Kleinknecht *et al.* (2014), Vergeer *et al.* (2015) and Wachsen and Blind (2016) all relied on data from a small country (The Netherlands) while Cetrullo *et al.* used industry-level data across EU-countries. Our paper used firm-level data from a large country (i.e., Germany). Consistent with these four studies, we find that the negative relationship between labor market flexibility and productivity growth holds in medium and highly cumulative sectors and mostly holds in the total sample. As expected, however, we find lower (and often insignificant) coefficients in industries with a low cumulativeness of knowledge.

We conclude that the standard narrative from supply-side economics for removal of labor market rigidities and more "flexibility" has a still sparsely noted downside. It might come at the cost of slower innovation and slower productivity growth in highly knowledge-intensive industries. This relates to a more general shortcoming of neoclassical theory: it has no theory of innovation. Since more than 150 years, neoclassical economists make the comfortable assumption that technology and innovation are "exogenous"; neoclassical theory then concentrates on (conditions for) utility maximization in an essentially *static* perspective. Neo-Schumpeterian theory, however, gradually developed a body of knowledge about determinants of innovation.

This new body of knowledge suggests that there is a trade-off between neoclassical *static* efficiency and Schumpeterian *dynamic* efficiency: what is 'good' for the efficient allocation of scarce resources can be 'bad' for innovation that makes resources less scarce. The holy grail of neoclassical theory is *Perfect Competition*, i.e., the concept of an ideal market. This ideal market always clears and scarce resources are allocated in a welfare-maximizing way. The policy message is: try through structural reforms to bring the market system as close as possible to the ideal of *Perfect Competition*. Even if the holy grail cannot be reached, one should at least avoid to be too distant from it.

Neo-Schumpeterian theory, however, suggests that *Perfect Competition* is *not* an ideal market for innovators. Innovation needs *im*perfect markets with entry barriers in various forms, such as patents, trademarks, copyrights, information asymmetries, network externalities, etc. Such entry barriers are required because innovators need to have the (expectation of) high monopoly profits in order to compensate for the high risks and uncertainties inherent to innovation. The bigger are the (expected) market imperfections and monopoly profits, the higher is the incentive to invest in risky and uncertain innovation projects.

There is one more reason of why perfect competition with large numbers of buyers and sellers is *no* milieu in which innovation prospers. Innovative projects typically have a cost structure that favors scale economies: high fixed (and sunk) costs for the first prototype, and then rapidly declining marginal costs during the diffusion process. This favors the emergence of large market shares and giant firms which is at odds with atomistic competition. In fact, innovation not only prospers under imperfect markets; it also produces market imperfections as its result.

Another problem with perfect competition is the assumption of efficient property rights. Knowledge behind innovation has strong properties of a public good and this makes it hard to protect such knowledge against imitators. We could interpret the creation of safe insider jobs with long job tenures (a labor market rigidity!) as one way to "buy" the loyalty of workers and thus to curb Pigouvian externalities. The latter is important as legal ways of protecting intellectual property (patents, trademarks or copyrights) only help to some degree, but are far from perfect.[1]

To conclude, after years of supply-side structural reforms of labor markets, major OECD countries now experience the lowest productivity growth since World War II. Supply-side economists expected the opposite: their reforms should make markets more "dynamic" and create stronger incentives for high performance. At first glance, a productivity crisis does not seem to fit into that picture. We argue it does.

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[1] The importance of loyalty of personnel for innovation is underlined by *Community Innovation Survey* data in the Netherlands. Brouwer and Kleinknecht (1999) found that among the mechanisms for protecting monopoly rents from innovation against imitators, "time lead on competitors" and "secrecy" ranked first and second. "Keeping qualified people in the firm" ranked third and "patent protection" only fourth. One should note that the second and third ranked factors depend on loyalty and commitment of workers that will erode under flexible hire and fire practices (see also Svensson, 2011).

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## Appendix I
## Descriptive statistics and random effects estimates

**Table A.1.** Descriptive statistics

| Variables | $N$ | Mean | Sd | Min | Max | Description |
|---|---|---|---|---|---|---|
| Log(Productivity) | 170 665 | 13.45 | 2.19 | 3.91 | 22.86 | Log of value added per working hour |
| % of temporary | 289 934 | 0.057 | 0.14 | 0 | 1 | % of fixed term contracts in the first half-year |
| % of terminated | 290 611 | 0.072 | 0.15 | 0 | 1 | % of terminated contracts in the first half-year |
| % of agency | 234 835 | 0.012 | 0.059 | 0 | 1 | % of agency workers in the first half-year |
| % of freelance | 247 314 | 0.012 | 0.074 | 0 | 1 | % of freelance workers in the first half-year |
| State of technical equipment | 274 133 | 3.77 | 0.779 | 1 | 5 | Assessment of overall technical state of the plant and machinery compared to the industry peers |
| Lnfirmsize | 291 656 | 3.17 | 1.86 | 0 | 11.00 | Log of total number of employees during the first half-year |
| Works council | 288 631 | 0.31 | 0.46 | 0 | 1 | 1 if the establishment has a work council, 0 otherwise |
| Independent | 353 132 | 0.59 | 0.49 | 0 | 1 | 1 if the establishment is independent, 0 otherwise |
| Age | 134 411 | 11.00 | 6.34 | 0 | 26 | Age of the establishment |
| Year | 353 132 | 2007 | 5.24 | 1998 | 2016 | Year |

**Table A.2.** Random effects estimates

| Variables | (Full sample) | (Low cumulative) $d.\log(y)_t$ | (High cumulative) $d.\log(y)_t$ |
|---|---|---|---|
| $\log(y)_{t-1}$ | −0.39*** (−58.45) | −0.24*** (−35.87) | −0.38*** (−40.58) |
| % temporary | −0.017*** (−2.65) | −0.0077 (−0.88) | −0.029*** (−2.47) |
| % temporary-sq | −0.0068 (−0.73) | −0.0061 (−0.51) | −0.004 (0.37) |
| % terminated | 0.0022 (1.03) | 0.0051 (−1.14) | 0.00038 (0.13) |
| % terminated-sq | 0.000* (1.93) | 0.0016 (0.95) | 0.0006** (2.25) |
| State of technical equipment | 0.0046*** (11.21) | 0.0049*** (9.66) | 0.0047*** (8.26) |
| Log (firm size) | 0.0433*** (55.29) | 0.028*** (34.77) | 0.0416*** (38.66) |
| Work council | 0.011*** (9.78) | 0.0034*** (2.88) | 0.0114** (6.96) |
| Independent | −0.0051*** (−5.26) | −0.0062*** (−5.34) | −0.0027** (−2.20) |
| % of agency | 0.056*** (6.21) | 0.021* (1.91) | 0.068*** (5.79) |
| % of agency-sq | −0.055*** (−3.57) | −0.010 (−0.46) | −0.070*** (−4.23) |
| % of freelance | 0.028*** (2.87) | 0.045*** (2.95) | 0.037*** (3.28) |
| % of freelance-sq | −0.0137 (−0.96) | −0.039* (−1.70) | −0.018* (−1.16) |
| % of part-timers | −0.0329*** (−20.17) | −0.023*** (−13.23) | −0.033*** (−15.05) |
| Age | −0.0004** (−2.21) | −0.00067** (−2.53) | −0.0005* (−1.76) |
| Age-Sq | 0.0000** (2.11) | 0.0000* (1.67) | 0.0000* (1.83) |
| Year-Dummies | Yes | Yes | Yes |
| Observations | 36 268 | 19 041 | 17 227 |
| Groups | 10 552 | 5644 | 5443 |
| R-squared | 0.38 | 0.39 | 0.38 |

*** = significant at 99% level;
** = significant at 95% level;
* = significant at 90% level.

## Appendix II

### Industries according to degree of cumulativeness of knowledge according to Peneder (2010, p. 331, Table 5)

**Industries with a *high* cumulativeness of knowledge:**
Chemicals; basic metals; machinery, nec.; electrical equipment, nec.; communication technology; precision instruments; motor vehicles, parts; financial intermediation; insurance, pension funding; computer services; research and development; other business services.
**Industries with a *medium* cumulativeness of knowledge:**
Mining (petroleum, gas); textiles; pulp/paper products; ref. petroleum, nuclear fuel; rubber and plastics; mineral products; computers, office machinery; other transportation equipment; manufacturing nec.; post, telecommunications.
**Industries with a *low* cumulativeness of knowledge:**
Mining (coal, peat, other); food & beverages; tobacco products; wearing apparel, fur; leather, leather products, footwear; wood, wood products, cork; publishing, reproduction; fabricated metal products; recycling; electricity and gas; water supply; wholesale trade; land transport, pipelines; water transport; air transport; auxiliary transport services; auxiliary financial services.

## Appendix III

### Choice of GMM estimator

Arellano and Bond (1991) performed specification tests that are applicable after estimating a dynamic model from panel data by the generalized method of moments (GMM). Difference GMM and system GMM are popular general estimators designed for situations with "small T, large N" panels, meaning few time periods and many individuals, for situations where independent variables are not strictly exogenous, meaning they are correlated with past and possibly current realizations of the error, on situations where there might be fixed effects, and cases that exhibit heteroskedasticity and autocorrelation within individuals/establishments (Roodman, 2009).

Blundell and Bond (1998) find that the difference GMM estimator is both biased and inefficient if the dependent variable is persistent. In the case of this paper, the log of value added per hour is non-stationary and persistent, and, in order to overcome this, the use of a system GMM is preferred. Roodman (2009) points out that the number of instruments in difference and system GMM tends to explode with time. If the number of observations is small, the cluster–robust standard errors and the Arellano–Bond autocorrelation test may be unreliable. However, given the high number of yearly observations in this paper, this should not be a problem. In fact, Roodman (2009) emphasizes that the validity of the additional instruments in system GMM depends on the assumption that instruments are uncorrelated with fixed effects.

As can be seen from the equations in Section 3, the dependent variable is the second order difference of the log of value added and unobserved fixed effects are no longer part of the model. The efficiency of the estimation is increased by augmenting the two-step difference GMM into a system. GMM-SYS involves a greater number of moment conditions than GMM-Difference, but in the case of persistence of the dependent there are benefits of using GMM-SYS over the difference GMM. The Arellano-Bond test tests for the existence of second-order autocorrelation in the first differenced error terms as represented in the model above. If found, in order to correct for it, the model can be augmented further with higher orders autoregressive lags. The Hansen test tests the validity of the imposed overidentifying moment conditions. Both these tests together can help us understand the validity of the GMM-SYS model.

As firms can adjust their share of temporary workers given their levels of productivity, fixed effect estimation might suffer from endogeneity issues driven from simultaneity bias. The GMM-SYS estimator overcomes the problem of endogeneity by instrumenting endogenous explanatory variables with both their lagged values and their lagged differences. Lagged variables took place before the productivity shock and as such cannot suffer from simultaneity bias. Following Hirsch and Mueller, 2012 and Arellano and Bond (1991), in order to improve precision, the model can be augmented with further lags from $t-2$ onwards as additional instruments.