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Are estimates of the "natural experiment" in the German crafts sector causal?

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Zusammenfassung:

In den letzten Jahren wurden viele Studien zu den Auswirkungen der Handwerksderegulierung von 2004 veröffentlicht. Die meisten dieser Studien nutzen Differenz-von-Differenzen-Schätzungen. Diese sind jedoch nur dann aussagekräftig, wenn sich Treatment- und Kontrollgruppe ohne die Deregulierung gleich entwickelt hätten (Parallel Trends-Annahme). Diese Annahme kann jedoch nicht geprüft werden. Die vorliegende Studie untersucht daher erneut die Auswirkungen der Deregulierung von 2004 auf die Markteintritte und -austritte von Handwerksbetrieben sowie den Anteil von Migranten und Einkommen. Im Gegensatz zu den Vorgängerstudien wird allerdings die synthetische Kontrollmethode angewendet, welche weniger starke Annahmen hinsichtlich der Entwicklung von Kontroll- und Treatmentgruppe macht.
Die Verwendung synthetischer Kontrollschätzungen ändert nichts an den Hauptaussagen der bisherigen Studien, sie lieferte allerdings einige interessante neue Erkenntnisse. Zusätzliche Informationen über die negativen Auswirkungen eines allgemeinen Konjunkturabschwungs auf den Markteintritt im Handwerk und die Integration von Migranten über das Handwerk konnten gewonnen werden. Zudem ist es interessant festzustellen, dass, obwohl der Differenz-von-Differenzen-Ansatz angemessen erscheint, um die Auswirkungen der Deregulierung im Handwerk im Jahr 2004 zu untersuchen, der Hinweis auf die Reform als „natürliches Experiment im Handwerk" nicht korrekt ist. Tatsächlich zeigt die Verwendung der alternativen Methode, dass Nicht-Handwerksberufe ebenfalls eine gute Kontrollgruppe bilden können.

Abstract:

Difference-in-difference estimation is a popular tool to gauge the effects of economic policies. In recent years, many papers have applied this tool to the German deregulation of the crafts sector in 2004 to draw lessons regarding the economic effects of occupational licensing. However, a difference-in-difference estimator is only valid when the treatment and comparison units would have evolved similarly in absence of the reform, an assumption which is non-testable. This paper investigates whether the policy insights based on existing studies hold water when the synthetic control method is used whereby comparison units are selected in systematic ways in order to resemble treated units. Overall, this robustness-check confirms the findings using difference-in-differences estimation, yet it also yields some interesting nuances notably regarding market exits.

Keywords: Synthetic control, Selection on observables, Occupational licensing, Craftsmanship
JEL: L51, J24, I28, M13

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1. Introduction

The German crafts sector presents researchers with a golden opportunity to examine the effects of occupational licensing since the scheme was recently reformed in a way that resembles a natural experiment. Prior to 2004, all German craft occupations were subject to a licensing scheme through the so-called "Meisterpflicht", a requirement to hold a Meister-title (an advanced vocational certificate) in order to found a company. The reform abolished the licensing scheme for certain craft occupations whereas others remain subjected to the traditional licensing scheme.

In recent years there has therefore been a surge of studies using the German crafts case and the deregulation in 2004 in other to examine economic effects of occupational licensing by means of the conventional difference-in-differences estimator (e.g. Rostam-Afschar, 2014; Runst et al. forthcoming; Runst, 2018; Koch and Nielen, 2016; Lergetporer et al., 2016; Damelang et al., 2017; Fredriksen, 2018).

Difference-in-differences estimation is a popular methodology among economists in order to gauge the effects of policy interventions that affect only a sub-group of the total population. A survey of economic studies published in 6 economic journals from 1990 to 2000 identifies 92 papers using this methodology (see Bertrand et al., 2004). There is good reason for this as it can circumvent the problem of unobserved heterogeneity. By comparing the difference in the treated group and the control group before and after a given intervention, the difference-in-differences estimator neither requires a perfectly randomized experiment nor controlling for systematic differences between the two groups.

However, the difference-in-differences estimator is only a casual effect of a given policy intervention when, in absence of the treatment, both treatment and control group would have followed the same trends over time, commonly referred to as the parallel trends assumption. A major concern in the policy evaluation is therefore whether in practice, the parallel trends assumption is plausible (Ryan et al., 2015).

A critical investigation of the validity of difference-in-differences estimation in the studies of the German crafts reform in 2004 has however so far not gone beyond standard placebo-tests. Yet, the parallel assumption depends on the non-treatment outcome for the treatment group after an intervention, which by definition is not observable, and hence it is in fact non-testable. Thus, investigating alternative methods that avoid this assumption altogether are warranted (Krief et al., 2016).

This study therefore re-examines the effects of the 2004 deregulation on market entry and exits, the share of migrants and incomes using the synthetic control method. Synthetic control estimation addresses the above-mentioned methodological concerns of conventional difference-in-differences estimation by carefully selecting comparison units in order to reduce bias. As such, this study contributes to the existing literature by investigating the robustness of results obtained.

The use of occupational licensing in the crafts sector is still part of the German policy debate und one of the leading parties (CDU) favors a reversal of the 2004 reform. Making sure that views on the deregulation are founded on solid scientific evidence is therefore important. Also, this paper contributes to a general debate on the reliability of difference-in-differences estimates. Given the frequent use of this methodology to advice policymakers on the effects of their actions, such research is warranted.

This paper is organized as follows: Part two acquaints the reader with the use of occupational licensing in the German crafts and existing studies on the deregulation that came into effect in 2004. Part three details the synthetic control method used as robustness-checks for current findings in the literature regarding the 2004 deregulation. Part four presents the results and part five concludes.

2. The German crafts sector and the 2004-reform

The German craft sector is regulated by the so-called Trade and Crafts Code (Handwerksordnung) and comprises about 5 million professionals in 93 trades[1], which make up about 12% of the working population.

The Meister-title plays an important role in the German crafts. It is the highest degree of vocational training and internationally recognized as tertiary education. In order to acquire it a professional must first undergo basic training (typically 3 years), which takes place both in a private company and in college, and become a so-called Geselle. Thereafter, additional training and exams involving occupation specific knowledge as well as knowledge about business management and pedagogy must be passed to acquire and associated exams in order to become a Meister, (see Mueller, 2014).

[1] The term "trade" pertains directly to the craft sector, whereas the term "occupation" is more general since a given occupation can contain both craft and non-crafts workers, as well as different craft trades. When referring to the German context, I will use the term "trade" to remain true to the German regulation. However, for insights on regulation, I will use the term "occupation" to align with the relevant literature.

Between 1953 and 2004, having a Meister-title was mostly a prerequisite to found a company in the crafts. The so-called “Hartz Reforms” of 2004 removed (fully or partially) the licensing requirements for certain trades in the German crafts sector.

Recently, a number of studies have been published that evaluate the economic effects of this reform (see Rostam-Afschar, 2014; Runst et al., forthcoming; Lergetporer et al., 2016; Koch and Nielen, 2016; Damelang et al. 2017; Zwiener, 1997; and Fredriksen, 2018). In particular, the studies by Runst et al. (forthcoming), Runst (2018) and Fredriksen (2018) are interesting since they rely on a novel classification scheme to isolate the crafts in population-wide datasets, which is vital in order to identify the effects of the policy intervention.

To summarize, these three studies provide policy-makers with the following insights: Removing occupational licensing leads to market entry, especially of low-qualified craftsmen, as well as market exits (Runst et al., forthcoming). The proportion of self-employed migrants as well as migrants employee increases, the latter effect however only concerns untrained individuals (Runst, 2018). No significant income effects of removing occupational licensing could be detected (Fredriksen, 2017).

Contrary to other case studies on occupational licensing, the German crafts studies could all exploit the fact that the reform only affected some individuals and therefore apparently provides researchers with a “natural” control group. Hence, common to these studies is a reliance on difference-in-differences estimation to gauge the effects of the 2004 regulation.

However, in contrast to laboratory experiments, natural experiments rarely fulfill the random treatment condition. In the case of the German crafts deregulation, the original bill relied on objective criteria such as hazardousness and contribution to vocational training in the crafts. If a trade was deemed to be potentially hazardous to third parties it would remain fully regulated or would only be partially deregulated and likewise if it made significant contributions to vocational training in Germany (see Bundestag, 2003a; and Bundestag, 2003b). Furthermore, there is evidence for interest group lobbying during the parliamentary discussions (see Bundestag, 2011; Bulla, 2012).[2] This speaks against random treatment assignment.

Yet, none of the existing studies on the German deregulation go beyond conventional difference-in-differences estimation. Possible identification problems are assessed based on outcome observations in the pre-treatment period, although what matters for casual interpretation is what might have occurred in post-reform period. Also, while the placebo-test is in most cases passed, Zwiener (2017) and Fredriksen (2018) find worrying indications of the opposite. A further cause for concern are the findings in Lergetporer et al. (2016), who attempt to correct for differences in the treatment and control group and as a result see their estimated reform effect on incomes greatly influenced.

This calls for a robustness-check of the established findings using data driven procedures to construct the best possible counterfactual, which is the aim of this paper. More specifically, insights from Runst et al. (forthcoming) on market entry and exit after the German reform as well as in Runst (2018) on migrant (self)-employment and Fredriksen (2018) on incomes, are proofed using the synthetic control method first introduced to the economic science in Abadie and Gardeazabal (2003) and Abadie et al. (2010).

Several papers have shown that this is a useful endeavor. In their pioneering work on the synthetic control method, Abadie et al. (2010) re-evaluate the effects of California’s tobacco control program and find much stronger effects that reported in earlier studies relying on cross-section estimates. In their re-analysis of a pay-for-performance initiative in the British health sector, Kreif et al. (2016) also uses the synthetic control method and find, in contrast to previous studies using difference-in-differences estimation, that mortality was not reduced and in some case even increased. O’Neill et al. (2016) re-examines the best practice tariffs scheme also in the British health sector using both the synthetic control method, a lagged dependent variable approach and matching on past outcomes. Finally, Peri and Yasenov (2018) using again the synthetic control method to confirm existing findings that influx of Cuban immigrants into Miami in 1980 had no effect on local wages.

3. Methodology

3.1 Data

To conduct the empirical analysis German microcensus data is used. There are several reasons for choosing the microcensus. Firstly, many of the existing studies on the 2004-deregulation use the microcensus and since this analysis complements existing results in the literature, it is preferable to use similar data set-up in order to achieve a comparable a robustness analysis.

[2] One member of parliament made the following statement concerning a trade which was intended to be deregulated: ”Surgical device mechanics [Chirurgiemechaniker] play an important role in my local election district. Many of them vote for SPD [Social Democratic Party]”, (Bulla, 2012).

Secondly, when attempting to make the treatment- and comparison groups as similar as possible, it is beneficial to have many potential covariates at disposal. The microcensus is a broad survey which covers personal information (gender, year of birth, family status, citizenship etc.), labor market information (labor market status, occupation), human capital accumulation (schooling, further qualifications), total net income, retirement provisions) and household characteristics (marital status, number of children etc.).

Finally, as always when making comparative policy analysis, it is important to have reliable and representative data. The German microcensus is a representative official sample survey of the German population. It covers 1% of the population and is conducted annually. The mandatory nature of the census survey guarantees a low rate of item-non-response for most questions.

If one is to assess the implications of a particular policy change in the crafts sector, it is paramount that the sample - and in particular the treatment groups - only comprise individuals within this sector. The microcensus does not contain direct information on whether a professional works in the crafts sector. However, craftsmen can be distinguished from non-craftsmen on the basis of the occupational classification code (KldB1992). Most existing studies on the German crafts deregulation do this by the "eye-balling method".

For the purpose of this paper, a more rigorous method first proposed in Runst et al. (forthcoming) for identifying the crafts is employed, which combines the occupation codes in the microcensus with data from the Federal Institute for Vocational Education and Training on the share of crafts apprentices within each occupational code. Only occupations where this share exceeds 60% are considered as crafts here, which excludes individuals in the agricultural or industrial or service sectors of the economy, which are unaffected by changes in crafts legislation.

Cleaners as an occupational group are also excluded from the sample as there are reasons to doubt that this occupation code in the dataset can be considered a craft trade.[3] Furthermore, owing to its size (45% of all individuals in deregulated trades in the microcensus dataset), wrongfully including the cleaner occupation would severely bias any general conclusions about the reform.

The traditional occupational licensing scheme was only ever relevant for self-employed. Hence, the analysis is mostly restricted to this sub-group. However, in the case of migrants, effects on the self-employed and their employees are assessed separately as the literature seems to suggest that in this case, employees might be indirectly affected by regulations directed at employers.

Lastly, as this analysis pertains to labor market participation, individuals younger than 18 or older than 66, are excluded from the sample.

Runst et al. (forthcoming), Runst (2018) and Fredriksen (2018) use the microcensus dataset with these same adjustments pooled for the period 2000-2010. For the synthetic control estimations, it is however necessary to transform the data into a panel dataset. Hence individual observations are first aggregated into one observation for each of the 92 occupations. Furthermore, all the 52 deregulated trades are then aggregated into one treated unit as suggested in Abadie et al. (2010). Finally, since the length of the pre-treatment period is particularly important for synthetic control estimations, the period considered is extended back to 1995, which yields 9 pre-treatment years.[4]

The final sample for the robustness-check presented in this analysis consists of ca. 1000-5000 observations (depending on the variable considered), one for each occupation at each point in time where 16 observations are in the treatment group. Table 1 provides a descriptive summary of the variables used for this study. The market exit and exit variables are constructed as described by Rostam-Afschar (2014), based on the non-mandatory question about the employment status in the previous year, by comparing the current employment status with the one in the previous year. This non-mandatory question was included before 2005 for 0.45 % of the German population and for 1 % of the German population in 2005 and 2009. The migrant variable is the likelihood of being a migrant. It is equal to one if an individual migrated to Germany at some point in their life and zero otherwise. The income of self-employed craftsmen is based on the answer to the question "how high was your personal net total income last month"?

[3] As in: P. Runst, J. Thomä, K. Haverkamp and K. Müller, ‚A replication of 'Entry regulation and entrepreneurship: a natural experiment in German craftsmanship' (forthcoming).

[4] In the case of market entry and exit, it was not possible to include the year 1996 due to a lack of observations.

Table 1: Outcome- and predictor means

	Average of all deregulated occupations	Average of all control occupations
Dependent variables		
Market entry	0,02	0,04
Market exit	0,13	0,18
Share of self-employed migrants	0,10	0,08
Share of all migrant employees	0,14	0,09
Share of untrained migrant employees	0,21	0,17
Incomes	1282,45	1583,26
Predictors		
Age	41,94	40,83
Male	0,62	0,65
Hours worked	37,28	37,77
Being married	0,61	0,59
Having children	0,41	0,41
Lower secondary school	0,68	0,49
Intermediate secondary school	0,22	0,22
University entrance qualification	0,10	0,30
No professional qualification	0,10	0,08
Vocational training	0,74	0,61
Advanced vocational training	0,13	0,12
University entrance qualification	0,03	0,19

Source: Microcensus 1995-2010.

3.2 The synthetic control framework

The synthetic control method relaxes the difficult parallel trend assumption necessary for unbiased difference-in-differences estimates. The general principle behind the method is to weight the outcomes of the comparison units in order to construct a superior counterfactual for the treated unit, with the weights being chosen such that the synthetic control best reproduces the outcome variable of the treated unit in the pre-treatment period. The set of possible comparison units is commonly referred to as "donor pool".

The formal framework[5] of synthetic control estimation can be summarized as follows: The method takes as starting point a balanced panel dataset with t=1,…,T. Pre-intervention periods are noted T0 and post-intervention periods are noted T1. This means that a treatment unit is exposed to the treatment during periods T0+1,…,T and not in the period 1,…,T0. The synthetic control is defined as a weighted average of the units in the donor pool. It is expressed as a (J x 1) vector of weights W=(w2,…,wj+1)', with 0≤wj≤1 for j=2,…,J and w2+…+wj=1.

The values of W are selected such that the characteristics of the treated unit best resemble the characteristics of the synthetic control. Consider X1, which is a (k x 1) vector containing the pre-intervention characteristics of the treated unit and X0, which is an identical vector for the units in the donor pool. The differences between the treated- and comparison units are then given by X1-X0W. The synthetic control selected, W*, minimizes the size of this difference.

$$\sum_{m=1}^{k} v_m (X_{1m} - X_{0m} W)^2$$

[5] The explanations and notations of the theoretical framework are identical to those in Abadie et al. (2010).

v_m is here the weight assigned to each control unit in the donor pool.

The synthetic control estimator is then given by the comparison between the outcome for the treated unit and the outcome for the synthetic control at that period. The outcome of unit j at time t is noted Yjt. Yi is a (T1 x 1) vector of the post-intervention values for the treated unit. Y0 is a (T1 x J) matrix containing the post-intervention values for the comparison units. The treatment effect is the given by:

$$Y_{it} - \sum_{j=2}^{J+1} w_j^* Y_{jt}$$

The synthetic control approach has many advantages. Firstly, it allows the effects of unobserved confounders to vary over time, by reweighting the comparison group so that it has similar characteristics as the treatment group. Difference-in-differences estimation in contrast assumes that the effects of confounding variables are constant over time. Secondly, synthetic control estimation is very transparent. It is apparent whether the treated unit is sufficiently matched by the synthetic control and on this basis, the analyst can decide whether or not to go forth with the analysis. With conventional difference-in-differences estimation, estimate uncertainty is commonly reported by the standard error. The standard error however gives no information about the overlap (or lack thereof) between the treatment- and the control group, although these models have been shown to perform poorly when it is not the case (see e.g. Dehejia and Wahba, 1999/2002).

The synthetic control method also has certain disadvantages. Notably, a systematic selection of comparison units can of course only be done on the basis of observed characteristics. Hence, idiosyncratic shocks affecting the outcome variable may make the synthetic control only appear similar and hence bias results. Abadie et al. (2010) show that this problem is alleviated when the pre-intervention period is long. In the case of the German crafts deregulation, our pre-treatment period is 9 years (from 1995 to 2004). Also, it will lead to a loss of observations as in our case individual observations need to be aggregated to the crafts trade level. However, this is a cost we are willing to pay as it has been said that “the main barrier to quantitative inference in observational studies is not the small-sample nature of the data, but rather the absence of an explicit mechanism that determines how comparison units are selected” (Abadie et al., 2015, p. 496).

3.3 Identifying predictors of the outcome variable

The synthetic control estimation is performed by the command synth in Stata. The program selects the comparison units, which are most similar to the treatment units based on observable characteristics that predict the outcome in the pre-treatment period. Researchers must however make the important choice of which predictors to include in the selection procedure. The principle aim is to include predictors that have a stable relationship with the outcome variable (McCelland and Gault, 2017). For the purpose of this analysis, several combinations of predictors are considered and the preferred predictor-specification will be the one with the lowest Root Mean Squared Percentage Error (RMSPE), which measures the pre-treatment fit.

An obvious predictor is the lagged outcome variable because most structural economic outcomes, and certainly those considered in this analysis, do not vary much over time. Also, the lagged outcome variable will capture unobserved characteristics that influence the outcome variable. Athey and Imbens (2006) argue that including other variables rarely matter. Hence, in a first set of specifications, lags of the outcome variables are the only predictors in the synthetic control estimation. The recommendation from Ferman et al. (2016) to try different sets of lags and report the results from all of them is here followed. A first estimation includes the first, middle and last lag of the outcome variable as predictor as Gault (2017) recommend including only a few lags. A second estimation includes the last three lags of the treatment period as predictors, which is one of the recommendations in Kaul et al. (2016). A final estimation, inspired by the recommendations in both Kaul et al. (2016)[6] and McClelland and Gault (2017)[7], includes lags of the two years when the outcome variable is closest to its average in the pre-treatment period.

It has been pointed out that if other observables outcomes help predict the outcome, omitting them can bias the synthetic control outcome in the post-treatment period (Kaul et al, 2016). This is a serious critic as it relates to the credibility of the counterfactual, which is the aim of the synthetic control method to ensure. In order to address this possibility, a second set of specifications uses both the above-mentioned combinations of lags and other economic variables from the microcensus dataset that have predictive power for explaining the dependent variable (subsequently called “covariates”) as predicators.

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[6] Kaul et al. suggest using an average of the outcome across all treatment years.
[7] McClelland et al. recommend choosing a small number of lags that follow the outcome trend in the pre-treatment period.

The findings in Heckman (1997) support a generous selection of covariates since the lowest bias values were obtained when the covariate vector included a rich set of variables relevant to modeling the probability of treatment. Also, Hahn and Shi (2017) recommend a relatively large number of predictors compared to the number of comparison units. Hence, the aim was to use all the significant covariates from the difference-in-differences in Runst et al. (forthcoming), Runst (2018) and Fredriksen (2018) as predictors. However, some control variables used in the original papers had to be dropped in order to be able to construct a synthetic control.

In the case of market entry and exit, the following covariates are included: Age, gender, a dummy for being married, a dummy for having children, education, professional qualification, a dummy for residing in former Eastern-Germany and the size of the resident city. In the case of migrants, the only covariates included are age, gender, marital status, the number of children and city size. Finally, in the case of incomes, the covariates included are age, age squared, gender, having a migration background, hours worked, highest obtained general education and vocational qualification, marital status and the number of children.

Concerns have been raised that including lagged outcomes as predictors may eliminate the effect of the other predictors (Kaul et al. 2016). A final predictor specification therefore only includes the covariates listed above as predictors without including lags of the outcomes. Due to the encompassing nature of the microcensus, the large number of variables at disposal should reduce the concern that important unobservable predictors are omitted.

For all these calculations, the donor-pool consists of both fully regulated trades and partially regulated trades. The reasons for this is that only considering the still fully regulated trades as comparison units would imply relying on very few craft observations in the control group. Also, previous studies typically find no reform effects in the partially deregulated trades. However, the sensitivity analysis addresses this issue further.

3.4 Sensitivity analysis

A general concern for comparative policy evaluation is that the intervention may have "spread" to units that were originally unaffected (Abadie et al., 2010). Avoiding such "tainted" units in the donor-pool is important for synthetic control estimation. The same procedure used in this paper to identify the crafts also sorts the German crafts trades into one of three groups: Fully deregulated in 2004, partially deregulated in 2004, or still regulated.

In the 52 occupations classified as fully deregulated trades, market entry is now free. These trades form the treatment group. The traditional licensing scheme remains unchanged for the 6 in the data categorized as still fully regulated. These are ideal comparison units; however there are few of them. The final 35 trades are classified as partially deregulated in 2004. For these trades, the law allows the crafts chambers to permit experienced employees without a Meister-degree to start a business.[8] Prerequisites to be granted permission are that the employee have worked in the field for six years or more and have worked in a managerial position for four years or more or intend to hire a third-party company manager that meets the same criteria.[9] An alternative specification removes these partially deregulated trades from the donor-pool.

Also, the policy literature has pointed out the danger of fake treatment effects (see e.g. Angrist and Krueger, 1999; Peri and Yasinov, 2018). This is particularly true with case studies that involve a small number of units of observation. Since the dataset had to be aggregated to the occupation-level in order to conduct the synthetic control method, a large observation loss occurred. Hence, as suggested in Abadie et al. (2003 and 2010), inference is analyzed through placebo tests. The placebo-tests are done using the specification including the best predictors and all occupations in the donor-pool. The basic idea is to apply the synthetic control method iteratively to every potential control in the donor pool (so-called "in-space placebos"). Thus, it becomes apparent if any treatment effect detected is large relative to the distribution of placebo effects estimated for occupations not affected by the deregulation.

4. Results

4.1 Results in the original studies using difference-in-differences

Runst et al. (forthcoming) find that as expected the reform did cause a surge of new entrepreneurship in fully deregulated trades since it is found that market entry has increased between 1.0 to 1.8 percentage points. Contrary to Rostam-Afschar (2014, 2015), which this study replicates among other things by using a different classification scheme for the crafts, no effect was found on market entry with regards to trades where occupational licensing still exists in a milder form. Also in contrast to Rostam-Afschar (2014, 2015) who finds no effect of the deregulation on market exit, Runst et al. (forthcoming) find that the deregulation has increased exit probabilities in the fully deregulated trades by between 2.0 and 2.5 percentage points.

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[8] HwO §7b, Altgesellenregel.

[9] Betriebsleiterregelung.

Runst (2018) concludes that the deregulation of occupational licensing has led to an increase in the proportion of self-employed migrants in the crafts sector. He finds an economically sizeable effect as the share of migrants has increased by 5 percentage points on average since the deregulation took place in the fully trades. Furthermore, it is found that the reform increased the likelihood of migrants to work as untrained employees in the crafts but not among highly trained employees or mid-range training levels. No significant effect of the reform was found on the share of migrants (whether self-employed or employed) in the trades that are still partially deregulated.

Fredriksen (2018) examine income effects only for self-employed and finds, contrary to Lergetporer et al. (2016) and Damelang et al. (2016), which also examine changes in incomes as a result of the deregulation, no convincing evidence of a significant negative effect. No overall significant negative effect on the incomes of all male craftsmen as a result of the deregulation in 2004. A closer look reveals that the deregulation appears to have reduced incomes by 6% in the construction crafts; however the standard placebo-test for parallel trends in the treatment and comparison group is not passed in this case. Surprisingly, a rather sizeable positive income effect for female craftsmen emerges, which is significant at the 10% level. However, also in this case, the placebo-test simulating an intervention in the pre-reform period is not passed.

These results using conventional difference-in-differences estimation is summarized in table 2.

Table 2: Overview of original studies

Study	Outcome variable	Main findings
Runst et al. (forthcoming)	1) Market entry	1) 1,0-1,8 percentage points higher entry in fully deregulated trades
	2) Market exit	2) 2-2,5 percentage points higher likelihood of market exit
Fredriksen (2017)	Net monthly income for self-employed	No overall significant effects on incomes of self-employed. Possible negative effects for males in the construction sector do not pass placebo-tests
Runst (2018)	1) Self-employed migrants	1) +5 percentage point higher share of migrants
	2) Total migrant employees	2) +4 percentage point higher share of migrants
	3) Untrained vs. trained migrant employees	3) 5-7 percentage points increase in the share of untrained migrants, no significant effects for trained migrants

Source: Original studies.

4.2 The synthetic control

The novelty of this study is to apply the synthetic control method to the German crafts case instead of difference-in-differences estimations. Hence, we begin the presentation of our results by looking at the obtained pre-treatment fit of the synthetic control estimations (RMSPE), which is useful when comparing different specifications of the same model, as well as the composition of the synthetic controls in the case of the different outcome variables.

The combination of predictors that yields the best pre-treatment fit varies between the estimations. It is however noteworthy the absolute differences between the estimated RMSPE values is not large, meaning that the choice of the predictor specification should a priori not have a large impact on the validity (or lack thereof) of the synthetic control method. Furthermore, predictor specifications that include both a covariates and a combination of lagged outcomes consistently perform best.

In the case of market entry, the preferred specification is combining the covariates from the microcensus dataset with the lagged outcome variables for the first, middle and last year of the pre-treatment period, see table 3 column 1. This particular specification yields a RMSPE of 0,00059. In the case of market exit, using covariates and the two outcome lags most similar to the pre-treatment mean gives the best fit, see table 3, column 2. For incomes the best the best fit (lowest RMSPE) is achieved using covariates as well as the outcome variable in the first, middle and last year of the pre-treatment period (table 3, column 6), which is also the case when the reform-effect on self-employed migrants is assessed (table 3, column 3). For the analysis of migrant employees, the best fit is achieved when using only covariates or covariates in combination with the two lagged outcomes closest to the pre-treatment year (table 3, column 4). The synthetic control estimations of the reform-effect on untrained migrant employees is the only case where relying solely on lagged outcomes yields the best pre-treatment fit (table 3, column 5).

Table 3: Pre-treatment fit

	RMSPE entry (1)	RMSPE exit (2)	RMSPE migrant self-emp (3)	RMSPE migrant employees (4)	RMSPE migrants untrained (5)	RMSPE incomes (6)
Only outcome lags						
LAG_A	0,00266	0,03410	0,00928	0,01053	0,03816	0,02691
LAG_B	0,00290	0,03332	0,00758	0,00813	0,02266	0,14187
LAG_C	0,00296	0,03269	0,00816	0,00575	0,04175	0,04048
Only individual characteristics						
vars	0,00279	0,09274	0,01146	0,00490	0,03921	0,02690
Combination of the above						
vars+LAG_A	0,00059	0,01858	0,00933	0,01004	0,05117	0,01781
vars+LAG_B	0,00177	0,01541	0,00999	0,00784	0,03206	0,02591
vars+LAG_C	0,00202	0,01208	0,01146	0,00490	0,03921	0,02456

Note: For Lag_A, the first, middle and last lags of the outcome variable are predictors. For Lag_B, the three last lags of the treatment period are predictors. For Lag_C, the two lags closest to the pre-treatment mean are predictors. For Lag_x+vars, lag specification x and covariates are predictors.

Source: Microcensus 1995-2010.

The composition of the synthetic control varies between the various specifications and outcome variables, which the tables in annex 1 clearly illustrate. For market entry, non-crafts occupations make up more than 2/3 of the synthetic control, whereas in the case of market exits, the synthetic control is solely comprised of craft occupations. In the case of incomes, non-crafts occupations is still one of the biggest contributors to the synthetic control, however in the preferred specification with covariates the main contributor are gunsmiths, an occupation with is part of the German crafts sector that was partially deregulated in 2004. In the case of migrants, very few occupations contribute more than 1% to the synthetic control. Among those that do, non-craft occupations again make up the most important part.

It is interesting to note that in some cases, the synthetic control is very diverse. We have chosen not to include occupations that contribute less than 1% to the synthetic control. A sum of weights far from 100 therefore indicates that many different occupations contribute in a minuscule way to the synthetic control. In most cases, these tiny contributions to the synthetic control aggregated actually makes up more than half of the synthetic control.

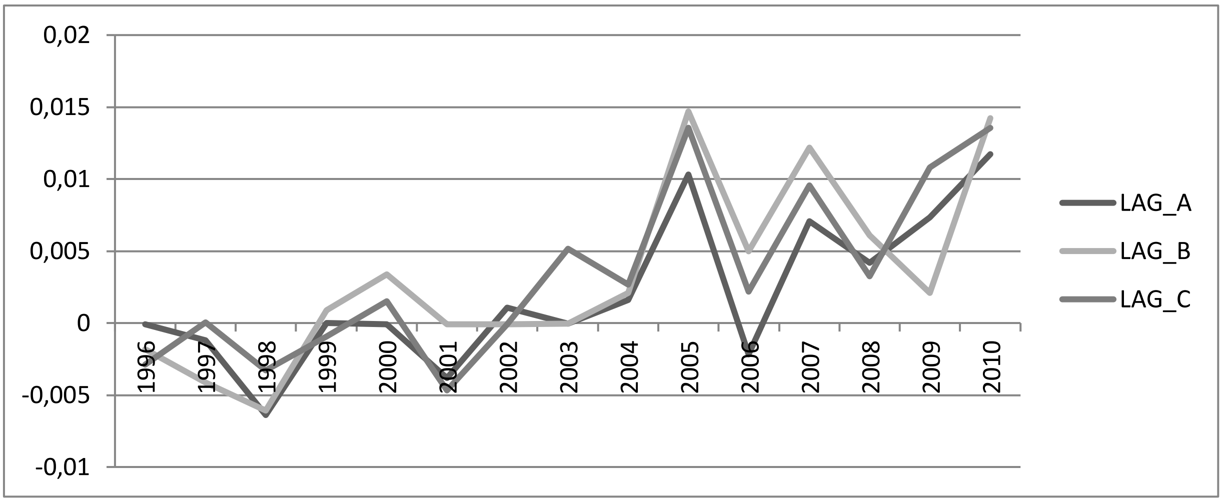
The fact that the synthetic controls predominantly consists of non-crafts occupations is also interesting. Whereas the three difference-in-differences studies highlighted in this paper do include non-craft occupations in the control group for sensitivity analysis, other published studies on the German crafts deregulation do not even consider non-crafts occupations in the analysis.

4.3 Effects of removing occupational licensing in the German crafts

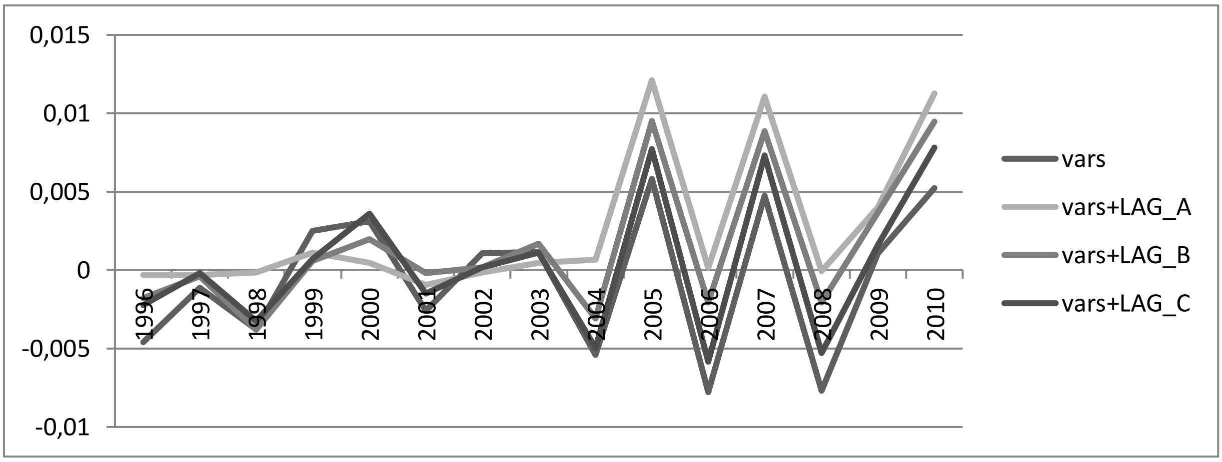
The already well-established negative link between occupational licensing and market entry are negatively is confirmed also with the synthetic control method. However, it is worth noting that while the market entry reform-effect (gap between deregulated trades and their synthetic control) is positive, it still evolves very erratically in the post-reform period (figure 1). It is interesting to note a drop around 2008, which was not visible in the original study using difference-in-differences that seems to indicate that market entry was negatively affected by the financial crisis

Figure 1: Gap in market entry between deregulated trades and synthetic control

A: Only lags as predictors



B: Combination of lags and covariates as predictors

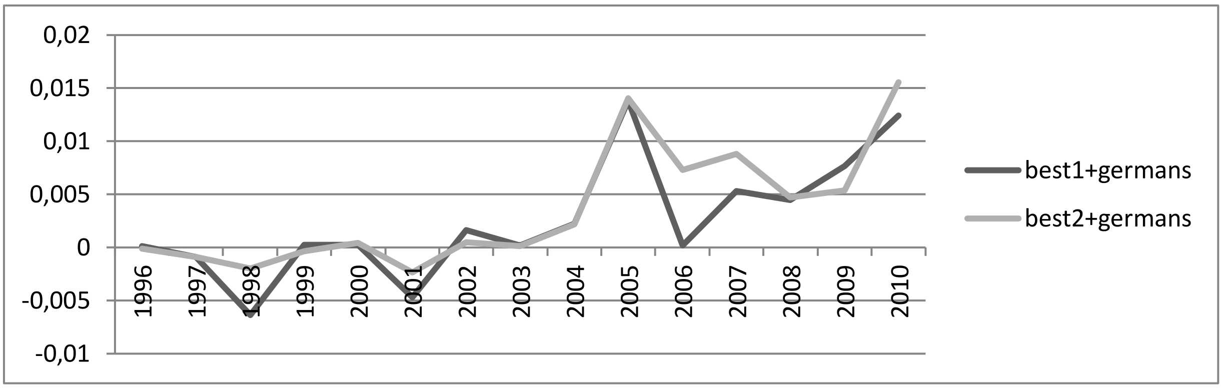


Note: For Lag_A, the first, middle and last lags of the outcome variable are predictors. For Lag_B, the three last lags of the treatment period are predictors. For Lag_C, the two lags closest to the pre-treatment mean are predictors. For Lag_x+vars, lag specification x and covariates are predictors.

Source: Microcensus 1996-2010.

It has been investigated whether the above-mentioned effect on market entry only concerns entrants from outside of German that have not had the same access to the German qualification system. In line with the findings in Runst et al. (forthcoming) and Rostam-Afschar (2014) we however also find that market entry has increased among self-employed craftsmen of German origin (see figure 2).

Figure 2: Gap in market entry between deregulated trades and synthetic control- Only German craftsmen



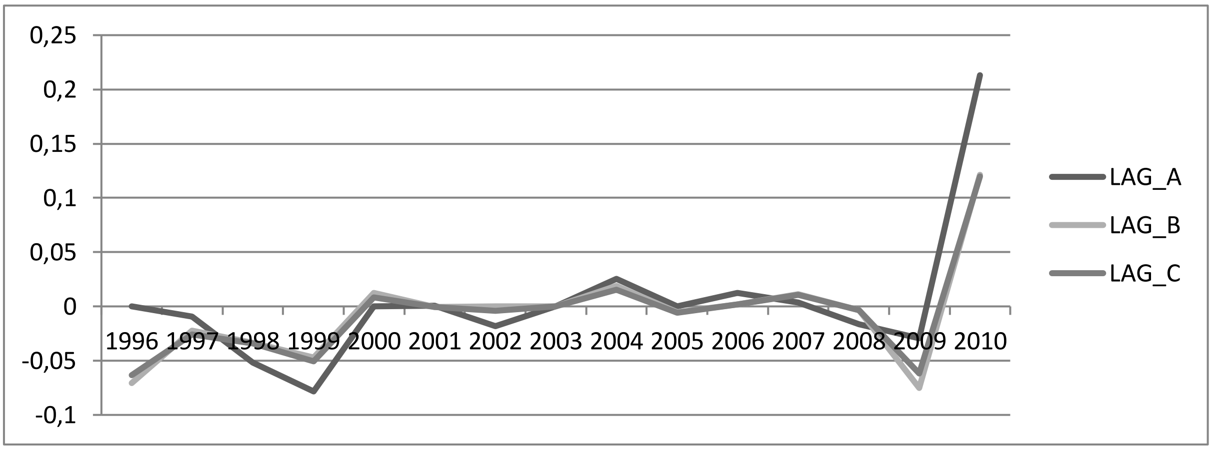
Note: Best1 refers to the specification with only lagged outcome variables as predictors that achieved the lowest RMSPE. Best2 refers to the specification with lagged outcome variables and covariates that achieved the lowest RMSPE:

Source: Microcensus 1996-2010.

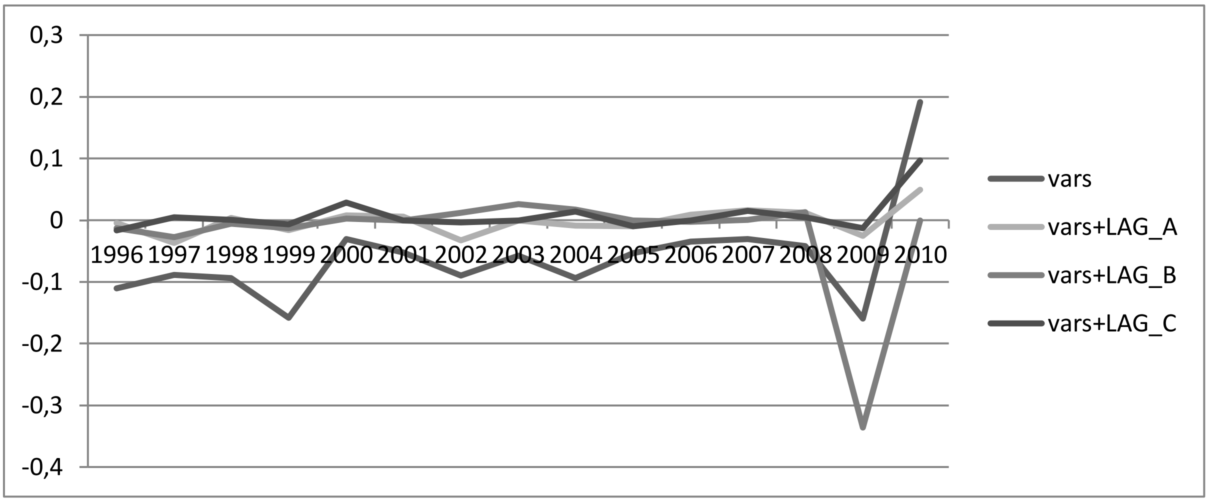
On the more controversial issue of market exit, we are unable to confirm the positive effect reported in Runst et al. (forthcoming), see figure 3. The synthetic control estimations appear rather to confirm the findings in Rostam-Afschar (2014) who could not detect any exit effects.

Figure 3: Gap in market exit between deregulated trades and synthetic control

A: Only lags as predictors



B: Both lags and covariates as predictors



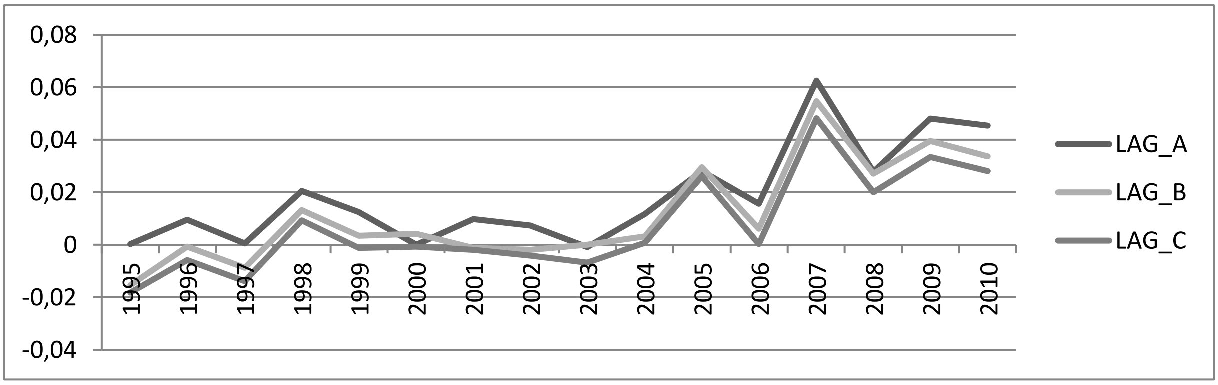
Note: For Lag_A, the first, middle and last lags of the outcome variable are predictors. For Lag_B, the three last lags of the treatment period are predictors. For Lag_C, the two lags closest to the pre-treatment mean are predictors. For Lag_x+vars, lag specification x and covariates are predictors.

Source: Microcensus 1996-2010.

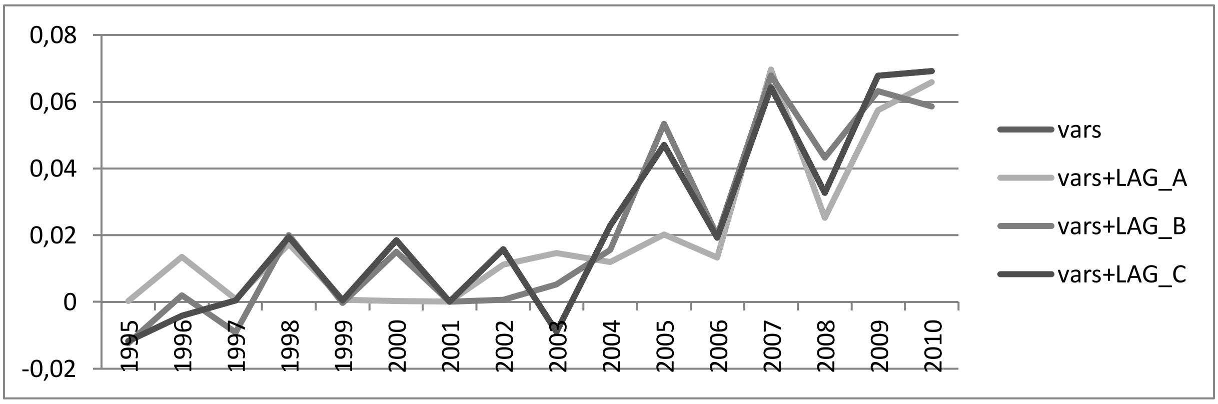
The share of self-employed migrants has more or less continuously increased since 2004 (figure 4), which is not surprising given that the traditional licensing requirement only concerned founding a company. Hence, this is the direct effect of the deregulation in 2004. However, the effect is almost as strong for migrant employees, which confirms the existence of an indirect effect of the regulation coming from employment practices (figure 5). Contrary to the findings in the original paper, an effect on untrained migrants cannot be detected (results not presented). However, this is likely due to the low number of observations in the synthetic control estimations when the sample is thus reduced.

Figure 4: Gap in the share of self-employed migrants between deregulated trades and synthetic control

A: Only lags as predictors



B: Combination of lags and covariates as predictors

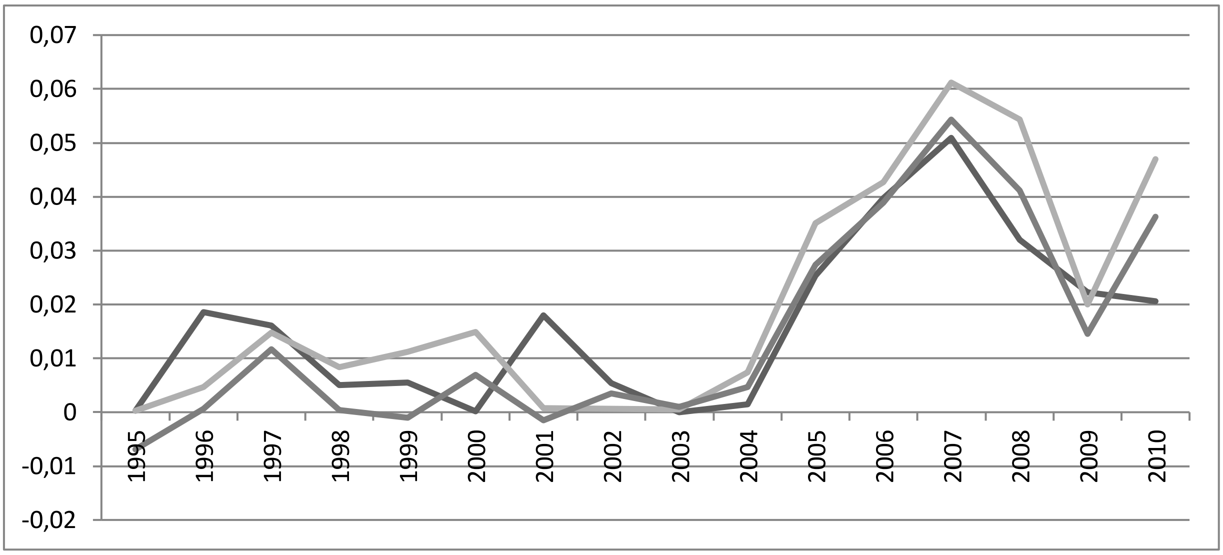


Note: For Lag_A, the first, middle and last lags of the outcome variable are predictors. For Lag_B, the three last lags of the treatment period are predictors. For Lag_C, the two lags closest to the pre-treatment mean are predictors. For Lag_x+vars, lag specification x and covariates are predictors.

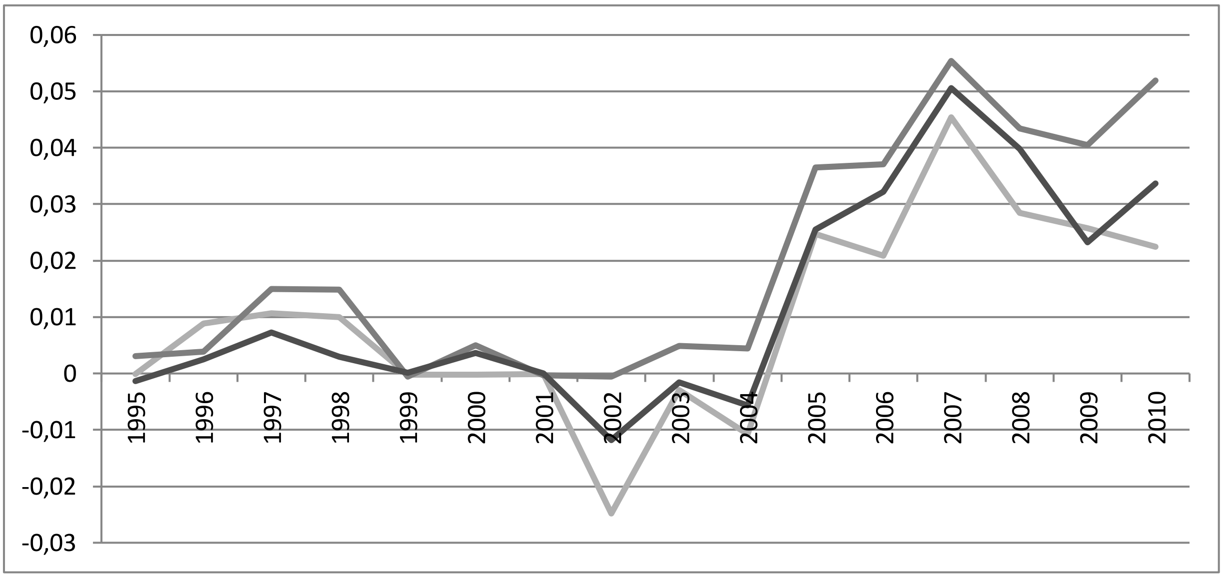
Source: Microcensus 1995-2010.

Figure 5: Gap in the share of all migrant employees between deregulated trades and synthetic control

A: Only lags as predictors



B Combination of lags and covariates as predictors



Note: For Lag_A, the first, middle and last lags of the outcome variable are predictors. For Lag_B, the three last lags of the treatment period are predictors. For Lag_C, the two lags closest to the pre-treatment mean are predictors. For Lag_x+vars, lag specification x and covariates are predictors.

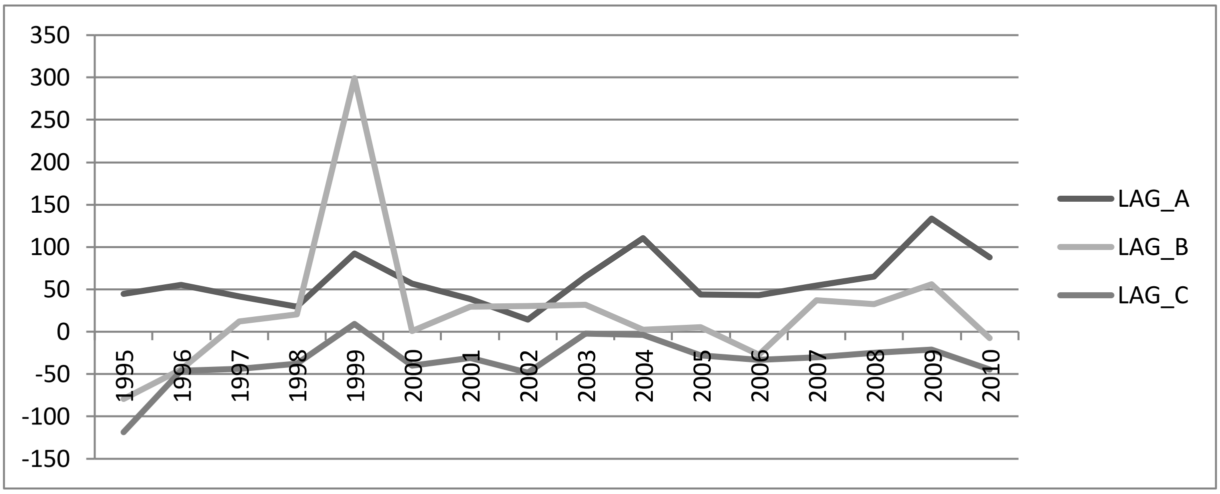
Source: Microcensus 1995-2010.

It is again interesting to note a drop in the share of migrants in the crafts sector in 2007/2008 that is not apparent in the difference-in-differences calculations in the original paper. Again, this is likely due to the financial crisis that worsened the general labor market situation in Germany in those years.

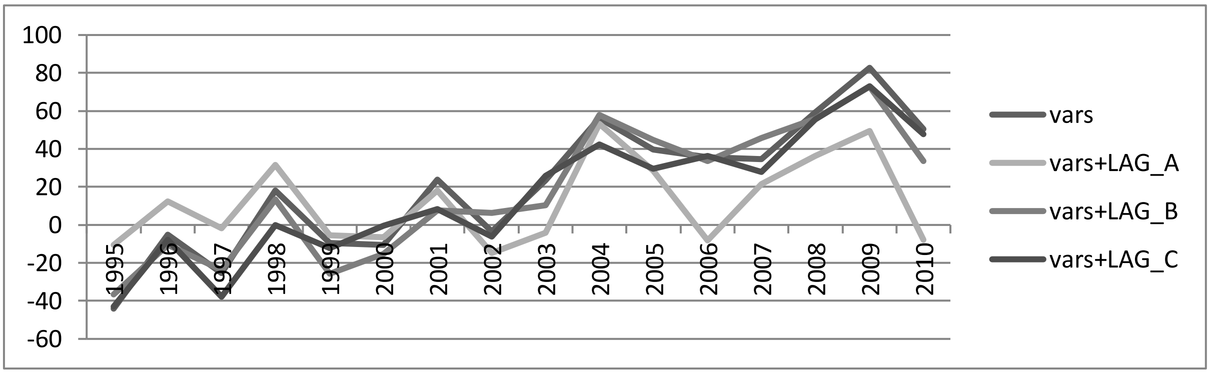
The income estimations are particularly interesting since here Fredriksen (2017) finds a result which is contrary to what the existing literature has claimed. Will the synthetic control estimation confirm no effect or will a negative effect of the deregulation emerge? The results show no decline in incomes as a result of removing occupational licensing in the German crafts sector (figure 6). If anything, there appears to be a rise in incomes in the specification where covariates are included as predictors (figure 6B).

Figure 6: Income gap between deregulated trades and synthetic control

A: Only lags as predictors



B: Both covariates and lags as predictors



Note: For Lag_A, the first, middle and last lags of the outcome variable are predictors. For Lag_B, the three last lags of the treatment period are predictors. For Lag_C, the two lags closest to the pre-treatment mean are predictors. For Lag_x+vars, lag specification x and covariates are predictors.

Source: Microcensus 1995-2010.

The results in Fredriksen (2018) suggest that male craftsmen working in the construction sector may have been (as opposed to all craftsmen seen together) affected by the reform. However, the synthetic control specification on this particular sub-sample (not presented here) yields very erratic curves, which may again be due to the loss of power when reducing the sample and a rather poor pre-treatment fit and it is our assessment that this specification does not add to the analysis.

Notice that in the case of incomes, the fit in the pre-treatment years is generally not fully convincing. The income difference between the deregulated trades and their synthetic control is large and varies substantially as opposed to being a constant line equal to zero which is desirable. Additionally, the specification with only individual characteristics and no lags (not shown here) was immediately dropped because of the lack of pre-treatment fit. Abadie et al. (2015, p. 500) warn “we do not recommend using this [aka: Synthetic control] method when the pretreatment fit is poor”.

There is no definition of "poor fit" in the context of synthetic control estimation. We therefore use a published study looking at incomes using synthetic control for reference. Peri and Yasinov (2018) in their analysis of the income effect of migration influx on incomes using synthetic control estimations obtain a maximum difference in the (log of) wage between the treatment- and synthetic control of about 0,07 points and characterize this pre-treatment fit as "reasonably good". In the case of the German crafts, the maximum difference in logs obtained is lower for all retained specifications, hence the pre-treatment fit is considered to be good enough to trust the results obtained.

4.4 Senstivity analysis

When we exclude the crafts occupations that were partially deregulated in 2004, our main results do not change, hence the donor-pool does not appear to contain treated units. The figures in annex 2 show that a reform-effect is still present for market entry and migrants whereas no effect is detected on incomes or market exits.

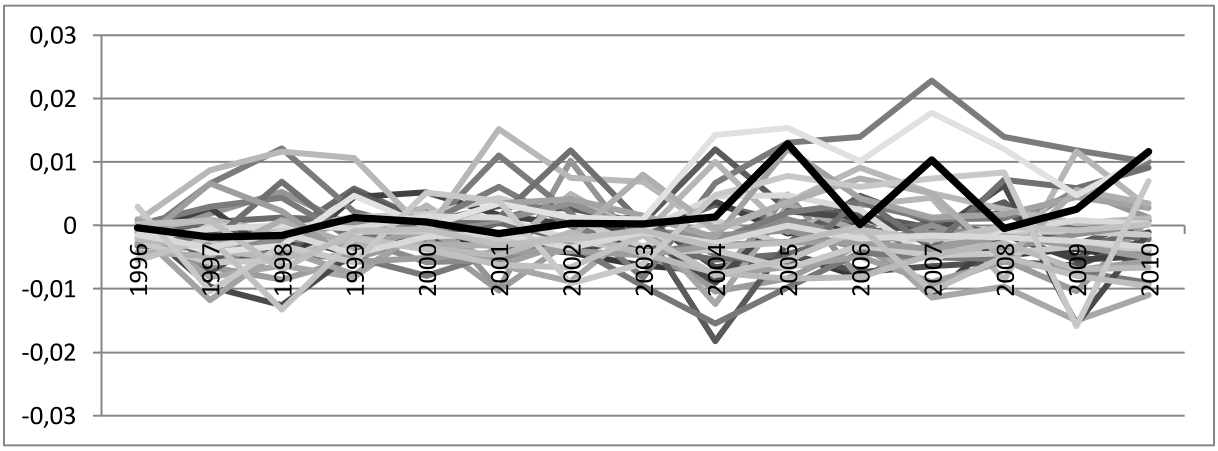
A number of placebo-test were furthermore conducted in order to check whether differences between treatment and control group can occur by pure chance. For these tests, similarly to the results presented before, the synthetic control method is applied successively to outcomes market entry, market exit, share of migrants and incomes. The donor pool consists of both fully regulated and partially deregulated crafts trades.

However, this time the treatment groups are all of the in reality untreated observations. This makes for a lot of treatment effects as the number of control occupations is large. We remove from the result figures placebo-interventions where the pre-treatment fit is particularly poor based on a comparison of their mean and standard deviation in the pre-treatment period to that of the true treatment group. This not only increases the visual interpretability of the resulting graphics, it is also in line with Abadie et al. (2010, p. 502) that point out that such placebo estimations „do not provide information to measure the relative rarity of estimating a large post-intervention gap".

The placebo-tests confirm the main findings in this paper. The gray lines in the graphs show the difference in outcome between each occupation in the donor pool and its respective synthetic version. The superimposed black line denotes this gap for the actual treatment group.

In the case of market entry, figure 7 shows that the true treatment effect shows one of the strongest increases compared to the synthetic control in the post-treatment period. In the case of market exit, figure 8 shows that the true treatment group does not stand out compared to the placebo-interventions. An exception to this are the last two years of the period under consideration where market exits in the true treatment group increase markedly compared to their synthetic control. However, whether this is due to the reform is uncertain since a time lapse of 5 years is considerable.

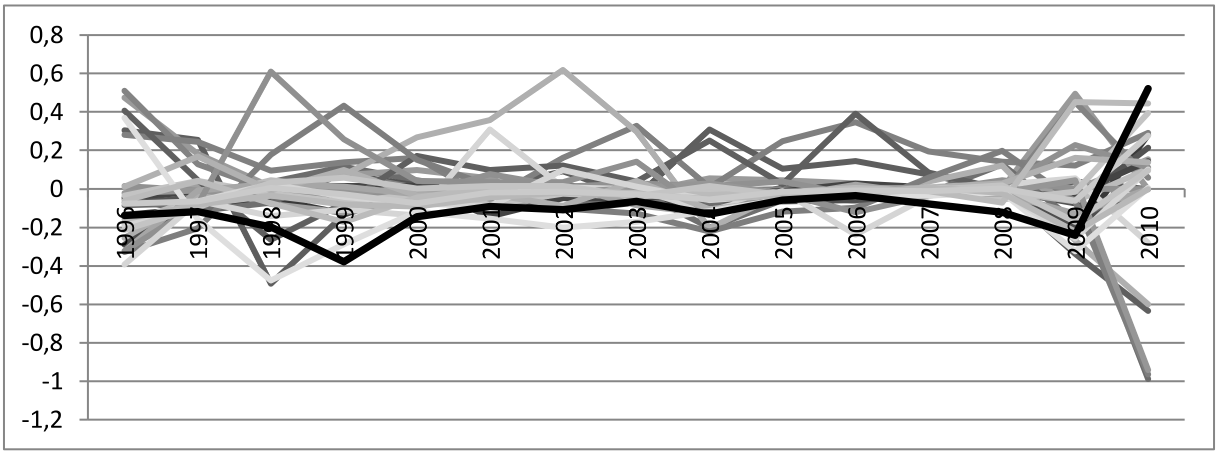
Figure 7: Gaps in the share of market entries in deregulated trades compared to synthetic control for 32 placebo interventions



Note: The predictor specification used is the combination of lagged outcome variables and covariates that yielded the lowest RMSPE.

Source: Microcensus 1995-2010.

Figure 8: Gaps in the share of market exits in deregulated trades compared to synthetic control for 28 placebo interventions

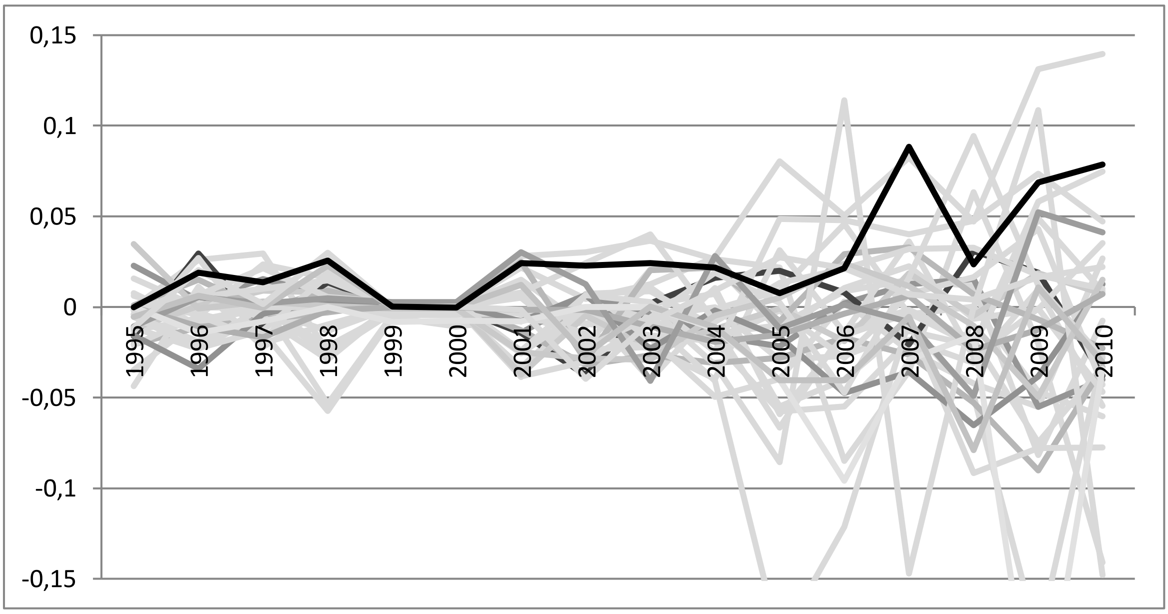


Note: The predictor specification used is the combination of lagged outcome variables and covariates that yielded the lowest RMSPE.

Source: Microcensus 1995-2010.

In the case of migrants, the placebo-test also suggests that the estimated treatment effect is a true treatment effect (see figure 9 and figure 10). These calculations for the sub-sample of untrained employees are left out as the calculations showed no treatment-effect for this group. The estimated gap for the deregulated trades during the post-treatment period is unusually large relative to the distribution of the gaps for non-affected occupations, a finding which is particularly true for all migrant employees.

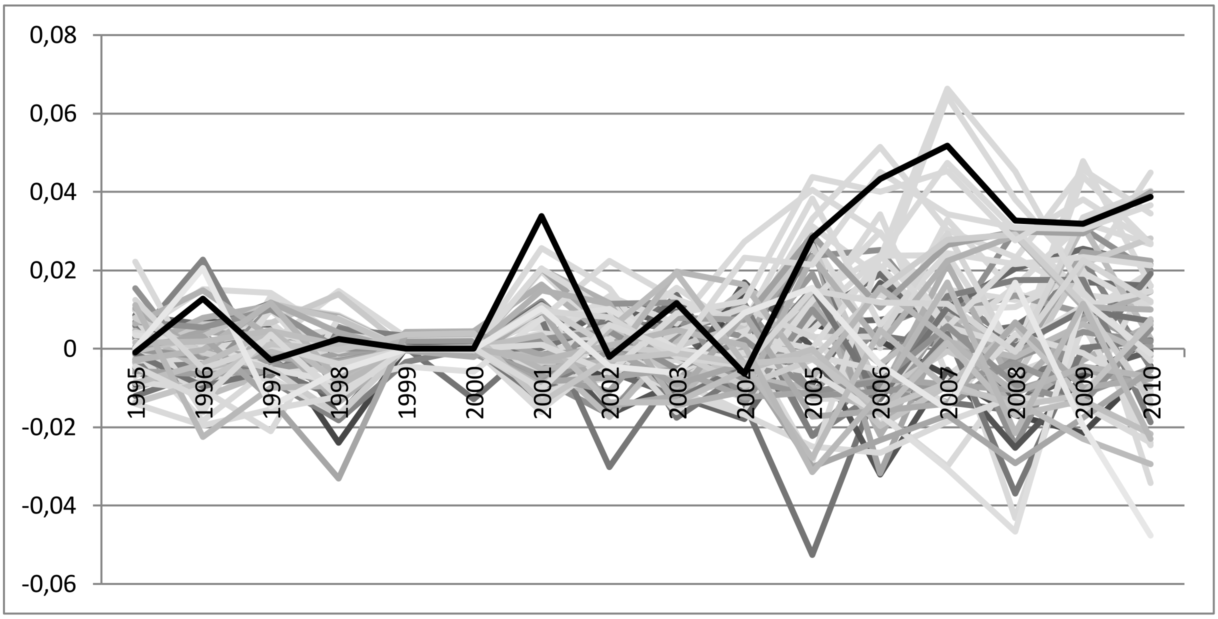
Figure 9: Gaps in the share of self-employed migrants in deregulated trades compared to synthetic control for 31 placebo interventions



Note: The predictor specification used is the combination of lagged outcome variables and covariates that yielded the lowest RMSPE.

Source: Microcensus 1995-2010.

Figure 10: Gaps in the share of migrant employees in deregulated trades compared to synthetic control for 59 placebo interventions

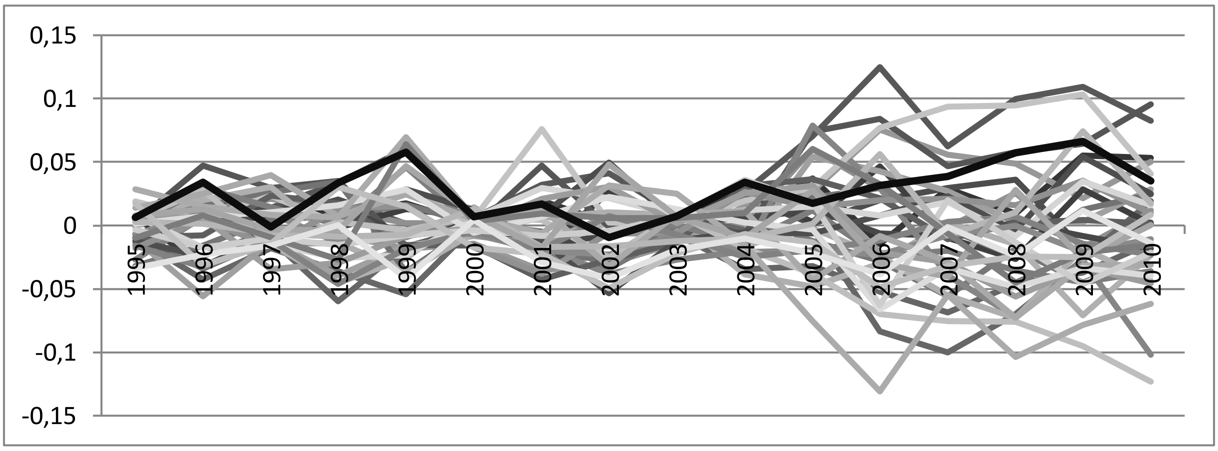


Note: The predictor specification used is the combination of lagged outcome variables and covariates that yielded the lowest RMSPE.

Source: Microcensus 1995-2010.

A placebo-test in the case of incomes seems less necessary as a treatment-effect could not be detected in the first place. Since an effect of occupational licensing on incomes has often been found in the literature, we however still present the placebo calculations in figure 11. Again, the true treatment group is represented by the black line. It appears evident that removing occupational licensing has not led to a decrease in incomes in deregulated trades, as one could have expected based on existing studies on occupational licensing. Possible reasons explaining this finding are detailed in Fredriksen (2018).

Figure 11: Income gaps to synthetic control for deregulated crafts trades and 35 placebo interventions



Note: The predictor specification used is the combination of lagged outcome variables and covariates that yielded the lowest RMSPE.

Source: Microcensus 1995-2010.

5. Conclusion

Using adequate comparison units is crucial in policy evaluation studies. If comparison units are not sufficiently similar to those subjected to the intervention of interest, any difference in the outcomes may simply be due to different characteristics of the groups.

O'Neill et al. (2016) find that there is no one policy evaluation methodology that delivers correct results in every situation. Based on this, the authors recommends "that the base case analysis should present results from the method(s) that uses the 'most plausible' identification assumption, but then the sensitivity analysis should present findings from method(s) that make alternative, but still 'somewhat plausible' identification assumption.

This paper has tried to accommodate the second part of this quote. Three existing studies looking into economic effects of removing occupational licensing regulation in certain German crafts trades in 2004 using difference-in-differences estimation are replicated using the synthetic control method. The latter methodology is an interesting tool to gauge the effects of economic policies since it constructs based on available data the best possible counterfactual and makes apparent whether an appropriate control could be created or not. Overall, using synthetic control estimation does not significantly alter conclusions drawn based on difference-in-differences estimations (table 4).

Table 4: Reform effects using synthetic control versus difference-in-differences

Outcome	Difference-in-differences estimation	Synthetic control estimation
Market entry	Increase	Increase
Market exit	Increase	No effect
Migrant self-employment	Increase	Increase
Migrant employment	Increase	Increase
Migrant untrained employment	Increase	No effect
Incomes	No effect	No effect

However, using a different methodology has provided some interesting new insights. Firstly, additional information was revealed regarding the negative effects of a general economic downturn on market entry in the crafts sector and migrant integration via the crafts. Secondly, the positive effect on market exit found in the original study does not appear to be robust. The reform-effect on market exits has been contested in the literature. The findings in this study confirm those in Rostam-Afschar (2014), the first study to use difference-in-differences in order to estimate the effects of the 2004-deregulation, that did not pick up any effect on exits. It should however be mentioned that the increase in exit found in Runst et al. (forthcoming) primarily stem from a specification using a different dataset. An alternative conclusion could therefore be that the microcensus is not suited to study market exits in the crafts. Thirdly, the previous finding that reform effects have been concentrated on untrained migrants could not be confirmed.

Finally, it is interesting to note that while difference-in-differences appears appropriate to study the deregulation in 2004, referring to the reform as a "natural experiment in the crafts sector" as Damelang et al. (2017) does is not correct. In fact, using a more transparent method like synthetic control estimation reveals that non-crafts occupations appear to be the better counterfactual. This shows that the issue of the counterfactual may be trickier than one might expect.

6. Literature

Abadie, A. and Gardeazabal, J. (2003), "The Economic Costs of Conflict: A Case Study of the Basque Country", in: American Economic Review, 93(1), 113-132.

Abadie, A., Diamond, A. and Hainmueller, J. (2010), "Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program", in: Journal of the American Statistical Association 105(490), 493-505.

Abadie, A., Diamond, A. and Hainmueller, J. (2015), "Comparative Politics and the Synthetic Control Method", in: American Journal of Political Science 59(2), 495-510.

Angrist, J.D. and Pischke, J.S. (2009), "Mostly Harmless Econometrics: An Empiricist's Companion", in: The Stata Journal 2(4), 358-377.

Athey, S. and Imbens, G.W. (2006), "Identification and Inference in Nonlinear Difference-in-Difference Models", in: Econometrica 74(2), 431-74.

Bertrand, M., Duflo, E. and Mullainathan, M. (2004), "How much should we trust difference-in-differences estimates?", in: Quarterly Journal of Economics 119(1), 249-275.

Damelang, A., Haupt, A. and Abraham, M. (2017), „Economic consequences of occupational deregulation: Natural experiment in the German crafts", in: Acta Sociologica, 1-16.

Dehejia, R. and Wahba, S. (1999), "Casual Effects in Nonexperimental Studies: Reevaluating the Evaluation of Training Programs", in; Journal of the American Statistical Association, 94(448), 1053-1062.

Dehejia, R. and Wahba, S. (2002), "Propensity Score-Matching Methods for Nonexperimental Causal Studies", in; The Review of Economics and Statistics, 84(1), 151-161.

Fredriksen, K. (2018), "Does occupational licensing really impact incomes? - The German crafts case", Ifh Working Paper Series.

Hahn, J. and Shi, R. (2017), "Synthetic Control and Inference", in: Econometrics, 5(4), 52.

Heckman, J. (1997), "Matching as an econometric evaluation estimator: Evidence from evaluating a job training program", in: Review of Economic Studies 64(4), 605-654.

Kaul, A., Kloessner, S., Pfeifer, G, and Schieler, M. (2016), "Synthetic Control Methods: Never Use All Pre-Intervention Outcomes as Economic Predictors", Working paper. Saarbuecken, Germany: Saarland University.

Kleiner, M (2006), "Licensing Occupations: Ensuring Quality or Restricting Competition?" Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.

Kleiner, M. M. (2015), "Border Battles: The Influence of Occupational Licensing on Interstate Migration", in: Employment Research Newsletter, 22(4), 4-6, W.E. Upjohn Institute for Employment Research.

Kleiner, M. and Kudrle, R. (2000), „Does Regulation Affect Economic Outcomes? The case of Dentistry", in: Journal of Law and Economics 43(2), 547-582.

Kleiner, M. and Krueger, A. (2010), „The Prevalence and Effects of Occupational Licensing", in: British Journal of Industrial Relations 48(4), 676-687.

Koch, A. and Nielen, S. (2016), "Oekonomische Effekte der Liberalisierung der Handwerksordnung von 2004", in: WISO Diskurs 05/2016, Friedrich Ebert Stiftung.

Kreif, N., Grieve, R., Hangartner, D., Turner, A.J., Nikolova, N. and Sutton, M. (2016), "Examination of the Synthetic Control Method for Evaluating Health Policies with Multiple Treated Units", in: Health Economics 25, 1514-1528.

Law, M. T. and Marks, M. S. (2009), "Effects of Occupational Licensing Laws on Minorities: Evidence from the Progressive Era", in: Journal of Law and Economic, 52, 351-366.

Lergetporer, P., Ruhose, J. and Simon, L. (2016), „Labor Market Effects of Entry Barriers to Self-Employment: Evidence from Deregulating the German Crafts Sector", Ifo Center for the Economics of Education, Ifo Institute.

McClelland, R. and Gault, S. (2017), "The Synthetic Control Method as a Tool to Understand State Policy", Research Report, Urban Institute.

O'Neill, S. Kreif, N., Grieve, R., Sutton, M. and Sekhon, J. (2016), "Estimating casual effects: Considering three alternatives to difference-in-differences estimation", in: Health Services Outcomes Research Methodology 16, 1-21.

Pashigian, P. B. (1979), "Occupational Licensing and the Interstate Mobility of Professionals", in: The Journal of Law & Economics, 22(1), 1-25.

Peri, G. and Yasenov, V. (2018), "The Labor Market Effects of a Refugee Wave: Synthetic Control Method Meets the Mariel Boatlift", in: The Journal of Human Resources, published online before print.

Rostam-Afschar, D. (2014), "Regulatory Effects of the Amendment to the HwO in 2004 in German craftsmanship", in: Empirical Economics 47, 1067-1101.

Rottenberg, S. (1962), „The Economics of Occupational Licensing", in: Aspects of Labor Economics, Princeton University Press, 3-20.

Runst, P. (2018), "Does the Deregulation of Occupational Licensing affect the Labor Market Participation of Migrants in Germany?", in: European Journal of Law and Economics, 45(3), 555-589.

Runst, P., Thomä, J., Haverkamp, K. and Müller, K. (forthcoming), "A replication of 'Entry regulation and entrepreneurship: a natural experiment in German craftsmanship", in: Empirical Economics.

Rubin, D. (1976), "Inference and missing data", in: Biometrika 63(4), 581-592.

Rubin, D. (1974), "Estimating casual effects of treatments in randomized and nonrandomized studies", in: Journal of Educational Psychology 66, 688-701.

Ryan, A.M., Burgess, J.F. and Dimick, J.B. (2015), "Why we shouldn't be indifferent to specification in difference-in-differences models", in: Health Service Research 50(4), 1211-1235.

Tullock, G. (2004), "The Selected Works of Gordon Tullock, Vol. 1: Virginia Political Economy", edited by Charles K. Rowley. Liberty Fund, Indianapolis.

Zwiener, S. (2017), "Essays on the German Labor Market", Dissertation Humboldt University, Berlin.

Annex 1: Composition of the synthetic control

The following tables show composition of the synthetic control for the specification with the lowest RMSPE both solely comprising of lags and the best-treatment fit with both lags and other covariates. Occupations that contribute to less than 1% of the synthetic control are not included.

Table A.1: Market entry

LAG_A		**vars+LAG_A**	
Occupation	Weight	Occupation	Weight
Non-crafts	61,2	Non-crafts	77,3
		Butcher	6,8
		Plasterer	9,3
		Chimney sweeper	6,1
Sum	61	Sum	100

Source: Microcensus 1996-2010.

Table A.2: Market exit

LAG_C		**vars+LAG_C**	
Occupation	Weight	Occupation	Weight
Non-crafts	0	Non-crafts	0
Precision mechanic	1,7	Precision mechanics	5,5
Metal worker	2,2	Installer and heating manufacturer	29
Plumber	3,1	Dispensing optician	11,6
Installer and heating manufacturer	3,1	Electrical technician	3,9
Automotive technician	3,1	Electrical engine manufacturer	1,6
Mechanic for agricultural and construction machinery	2,9	Baker	4,7
Gunsmith	2,7	Hairdresser	43,7
Dental technician	3,4		
Dispensing optician	3,6		
Orthopaedic technician	1,8		
Electrical technician	3,8		
Electrical engine manufacturer	2,3		
Hearing aid acousitician	3,1		
Communication technician	1,3		
Baker	3,5		
Butcher	27,1		
Oven and air heating manufacturer	2,3		
Hearing aid acousitician	1,6		
Roadbuilder	2		
Thermal and acousticinsulation fitter	3,3		
Glazier	2,3		
Carpenter	4,5		
Roof tiler	2,8		
Joiner	4,6		
Hairdresser	4,5		
Sum	97	Sum	100

Source: Microcensus 1996-2010.

Table A.3: Migrants- Self-employed

LAG_B		vars+LAG_A	
Occupation	Weight	Occupation	Weight
Non-crafts	2,1	Non-crafts	40
		Mechanic for tyres and vulcanization	1,1
		Gunsmith	1,9
Sum	2	Sum	43

Source: Microcensus 1995-2010.

Table A.4: Migrants- All employees

LAG_C		vars+LAG_C	
Occupation	Weight	Occupation	Weight
Non-crafts	28,1	Non-crafts	43,7
Sum	28	Sum	44

Source: Microcensus 1995-2010.

Table A.5: Migrants- Untrained employees

LAG_B		vars+LAG_B	
Occupation	Weight	Occupation	Weight
Non-crafts	24,7	Non-crafts	45,2
		Mechanic for tyres and vulcanization	1,1
		Precision mechanic	6,7
Sum	25	Sum	53

Source: Microcensus 1995-2010.

Table A.6: Incomes

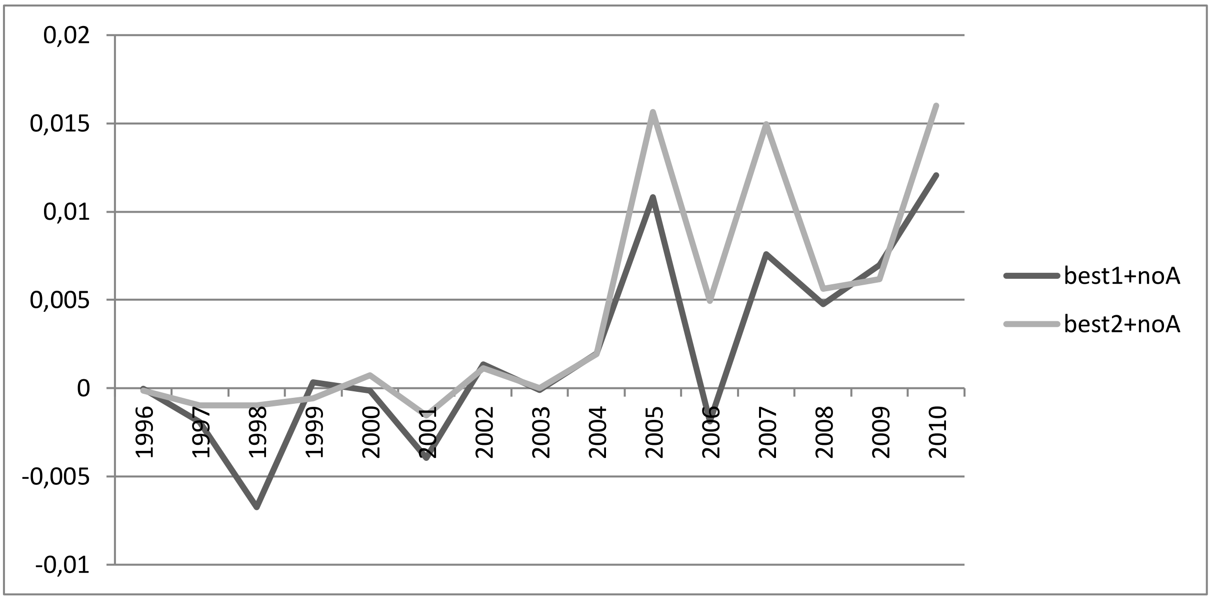
LAG_A		vars+LAG_	
Occupation	Weight	Occupation	Weigh t
Non-crafts	30	Non-crafts	24,4
Glass blower and glass apparatus builder	16,4	Glass blower and glass apparatus builder	6,7
		Metalworker	1,2
		Coachbuilder	1,9
		Gunsmith	36,1
		Orthopaedic technician	6,4
		Painter and laquerer	2,9
Sum	46	Sum	80

Source: Microcensus 1995-2010.

Annex 2: Composition of the donor pool

The following figures show the gap between the deregulated trades and their synthetic control when the trades that where partially deregulated in 2004 (referred to as A-trades) are excluded from the donor pool.

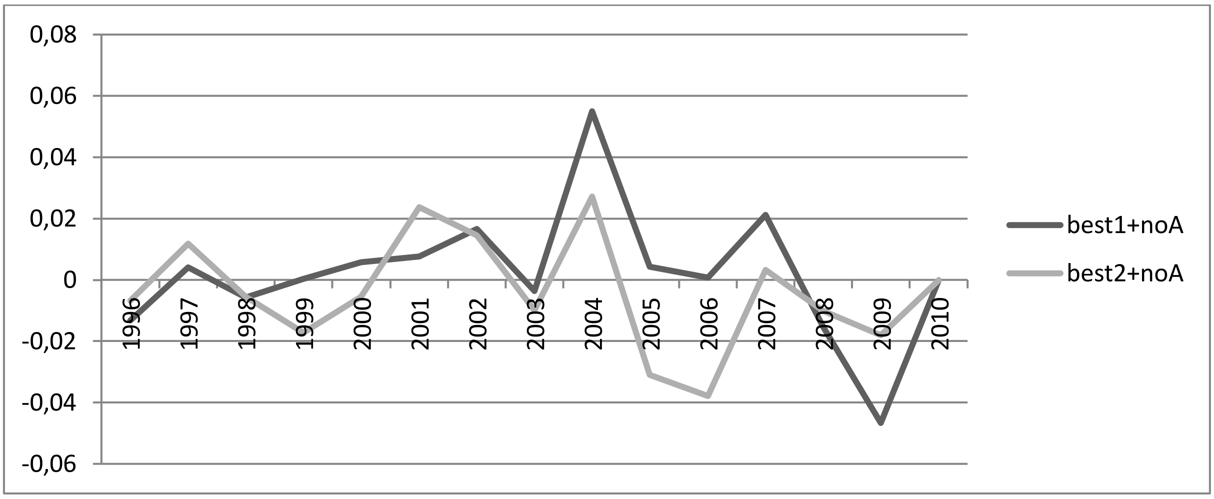
Figure A.1: Market entry



Note: Note: Best1 refers to the specification with only lagged outcome variables as predictors that achieved the lowest RMSPE. Best2 refers to the specification with lagged outcome variables and covariates that achieved the lowest RMSPE:

Source: Microcensus 1996-2010.

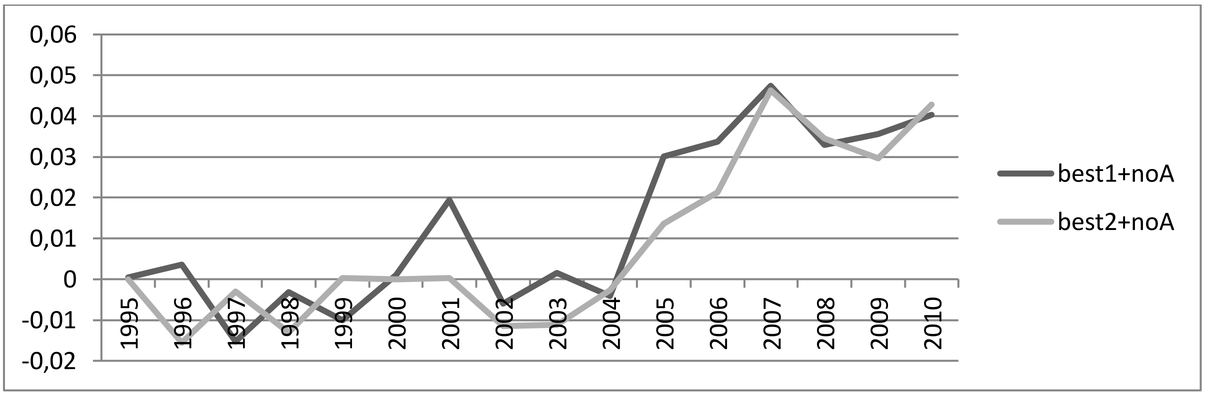
Figure A.2: Market exit



Note: Note: Best1 refers to the specification with only lagged outcome variables as predictors that achieved the lowest RMSPE. Best2 refers to the specification with lagged outcome variables and covariates that achieved the lowest RMSPE:

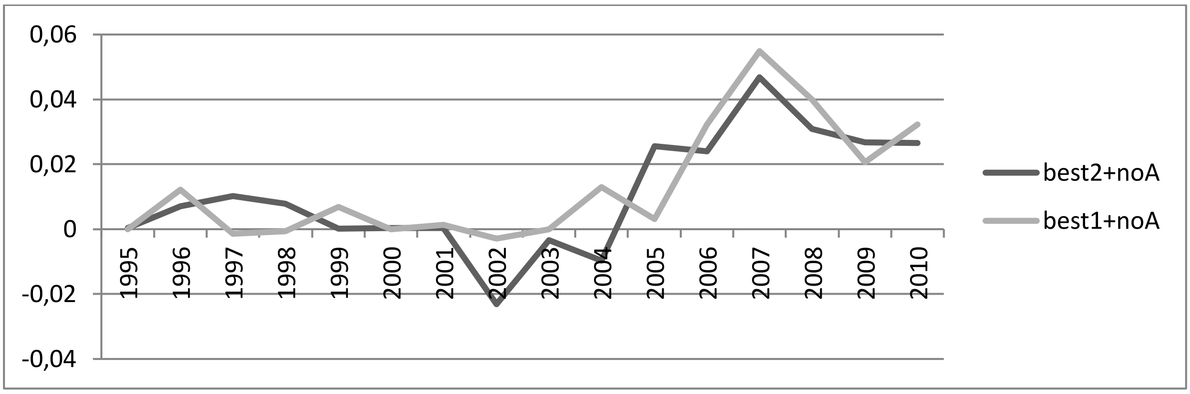
Source: Microcensus 1996-2010.

Figure A.3: Migrants- Self-employed



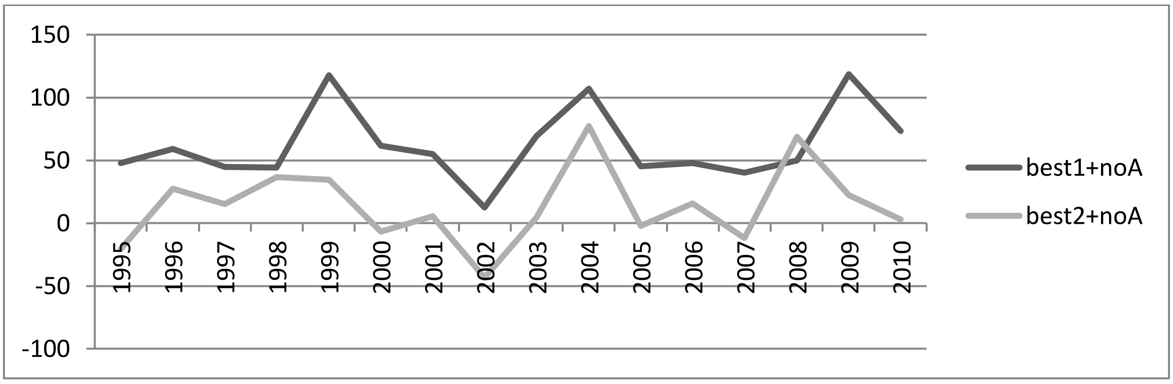
Source: Microcensus 1995-2010.

Figure A.4: Migrants- Employees



Source: Microcensus 1995-2010.

Figure A.5: Incomes



Note: Note: Best1 refers to the specification with only lagged outcome variables as predictors that achieved the lowest RMSPE. Best2 refers to the specification with lagged outcome variables and covariates that achieved the lowest RMSPE:

Source: Microcensus 1995-2010.