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Contents

Abstract

This paper analyzes whether financial disincentives affect firm demand for disabled workers. In Germany, firms must pay a noncompliance fine if they do not meet their legal quota for disabled workers. I exploit a threshold in this quota: Firms with fewer than 40 employees are required to employ one disabled worker, whereas firms with 40 or more employees must employ two disabled workers. Using administrative firm data, my results suggest that firms respond partially to the threshold and employ 0.388 more disabled workers when they are located just above the threshold. The effect remains positive after correcting for bunching behavior.

Zusammenfassung

In Deutschland müssen Unternehmen eine Ausgleichsabgabe zahlen, wenn sie die gesetzliche Quote zur Beschäftigung von Menschen mit Schwerbehinderungen nicht erfüllen. Im vorliegenden Papier wird untersucht, inwieweit die Ausgleichsabgabe die Arbeitsnachfrage von Unternehmen beeinflusst. Dabei nutze ich eine Schwellenwertregelung innerhalb der Schwerbehindertenquote: Unternehmen mit mindestens 20, aber weniger als 40 Beschäftigte müssen mindestens eine Person mit Schwerbehinderung beschäftigen, Unternehmen mit mindestens 40, aber weniger als 60 Beschäftigte müssen mindestens zwei Menschen mit Schwerbehinderungen beschäftigen. Mit Hilfe administrativer Unternehmensdaten schätze ich den Schwellenwerteffekt auf die Anzahl der Personen mit Schwerbehinderungen im Unternehmen. Meine Ergebnisse zeigen, dass Unternehmen zum Teil auf die Regelung reagieren und im Durchschnitt 0,388 mehr Personen mit Schwerbehinderungen beschäftigen, wenn sie sich knapp oberhalb des Schwellenwertes befinden. Dieser Effekt bleibt auch dann positiv, wenn berücksichtigt wird, dass manche Unternehmen bewusst unterhalb der Schwelle bleiben.

JEL

J15, J21, J23, J71, J78

Keywords

disability, employment quota, noncompliance fine, administrative data

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Availability of data

In this paper I use proprietary data that is held by the Institute of Employment Research (IAB). Since this data is of administrative origin, access is subject to legal restrictions under the laws of the Ger-man Social Code. Therefore, the data is not freely available to the research community. However, all the datasets and codes of this paper will be archived at IAB exclusively for the purpose of replication.

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Conflict of Interest

None declared.

1 Introduction

Low levels of employment and high rates of unemployment reflect the considerable labor market disadvantages of individuals with disabilities in all OECD countries. In the late 2000s, the unemployment rate among individuals with disabilities was twice as high as that among individuals without disabilities (14% compared to 7%) (OECD, 2010). Furthermore, many employers prefer to pay a fine instead of employing individuals with (severe) disabilities. In Germany, approximately 27 percent of private employers with 20 or more employees preferred paying a noncompliance fine to employing any worker with a disability in 2019 (Federal Employment Agency, 2021). In addition to discrimination tendencies and prejudices, employers may anticipate higher costs when considering hiring an individual with a (severe) disability. Such individuals may need special workplace equipment, are often subject to special employment protection regulations, take more vacation time and, on average, have higher rates of absence due to illness (Hiesinger/Kubis, 2022).

To improve the integration of disabled individuals into the labor market despite these costs, many OECD countries have implemented policy reforms, often in the form of a mandatory employment quota combined with a monetary fine in the case of noncompliance. Even though employment quotas and noncompliance fines are widely used policy instruments for integrating individuals with severe disabilities into the labor market, surprisingly little is known about their effectiveness.

This paper attempts to analyze the intended and unintended effects of the employment quota for disabled workers. I exploit a threshold in the German labor law that sets the mandatory employment quota: Employees that are below the 40-employee threshold but have at least 20 employees are obliged to employ at least one disabled individual. Above this threshold, employers must employ at least two disabled individuals. My empirical analysis consists of two parts. First, I analyze whether employers (i.e., firms) manipulate their employment levels and purposely stay – or bunch – below the threshold to avoid the fine. I refer to this as the *unintended* effect of the quota. Second, I estimate the *intended* effect of the quota, which is the effect of the threshold on the number of disabled workers in a firm. For this, I follow Lalive/Wuellrich/Zweimüller (2013) and adopt a threshold design which is closely related to a regression discontinuity design (RDD). However, as I do find evidence of bunching, the naive threshold effect is potentially biased. Quantifying the magnitude of the bunching effect helps me to assess this bias and to bound the threshold effect.

Understanding the intended and unintended effects of any employment quota is crucial for two reasons. First, along with antidiscrimination legislation, mandatory employment quotas are one of the most common policies for integrating disabled workers into the labor market, as they are used in many OECD countries (OECD, 2003, 2010). While the effects of antidiscrimination policies have been quite well explored, there is a remarkable paucity on the effects of employment quotas on firm demand for disabled workers. Given the alleged importance of these quotas for integration, this paucity is striking. Second, my study helps to better understand the role of employment quotas and financial disincentives for labor demand in general. The threshold in the regulatory employment quota implies a sharp change in relative labor costs for different firms near the threshold. Thus, this policy allows me to study the behavior of firms facing this discontinuity. In so doing, I explicitly address the unintended effects of the employment quota, such as adjustments in the (nondisabled) workforce composition or changes in firm dynamics near the threshold. I further differentiate between firms that face different costs at the threshold depending on the extent of their compliance with the quota regulation.

To date, few studies have addressed the impact of an employment quota on firm dynamics and on firm demand for disabled workers. A large number of studies have looked at either the effects of antidiscrimination legislation with respect to workers with disabilities (see, for example, Acemoglu/Angrist, 2001; Beegle/Stock, 2003) or the impact of disability policies on the employment of disabled workers from a labor supply perspective (see, for example, Verick (2004) and Lechner/Vazquez-Alvarez (2011) for Germany or Barnay et al. (2019) for France). However, to the best of my knowledge, only three studies have evaluated the effect of a disabled worker quota on employment decisions from a labor demand perspective.

Lalive/Wuellrich/Zweimüller (2013) examine whether there is a discontinuity in the employment of disabled individuals between firms below and above the Austrian employment quota, which kicks in when a firm reaches 25 nondisabled workers. The authors find that firms react to the quota in two ways. First, firm demand for disabled workers increases above the threshold. Second, some firms manipulate their employment of nondisabled workers and purposely stay below the threshold. Despite this manipulation, the lower bound of the threshold effect remains positive. Similarly, Wagner/Schnabel/Kölling (2001) and Koller/Schnabel/Wagner (2006) examine firm dynamics at quota thresholds in Germany. While Wagner/Schnabel/Kölling (2001) do not find any evidence that there is an effect on employment growth at the first threshold within the employment quota, Koller/Schnabel/Wagner (2006) find evidence that employment growth slows slightly just before the second threshold. Wagner/Schnabel/Kölling (2001) argue that according to their results, the (first) threshold in the German disabled worker law "does not seem to have the kind of strong negative influence on job dynamics in small firms that is often attributed to it in public debates" (p. 10).

I extend this scarce literature on employment quotas and labor demand and study the German case in more detail. I contribute to the literature in two ways: *First*, I revisit the findings obtained by Wagner/Schnabel/Kölling (2001) and Koller/Schnabel/Wagner (2006) and analyze the German employment quota with a high-quality data set that has more precise information on firm size according to the disabled worker law and the number of disabled workers in a firm. As both Wagner/Schnabel/Kölling (2001) and Koller/Schnabel/Wagner (2006) use establishment-level survey data – and combined with administrative data in the case of Koller/Schnabel/Wagner (2006) – , these studies are based on only a small number of observations (approximately 300-400 establishments). Due to data restrictions, Wagner/Schnabel/Kölling (2001) do not have information on the number of workers with disabilities in each establishment. Furthermore, that study could only approximate the number of workers in each establishment on the basis of the disabled worker law and thus probably suffers from measurement error.

In contrast, the data used in the present study – the Official Employment Statistics on Severely Disabled People – are based on the notification procedure used by the German Federal Employment Agency to determine compliance with the employment quota. Thus, this data set contains firm size information that is consistent with the definition of firm size stipulated in the German disabled worker law.[1] The data set contains information on *all* German firms subject to the employment obligation (i.e., firms with 20 or more employees). Thus, my analyses are based on a vast number of observations. Combined with an additional administrative data set from the Federal Employment Agency, namely, the Establishment History Panel (BHP), I am able to describe all German firms around the firm size thresholds and each firm's workforce in great detail.

Second, while being closely related to Lalive/Wuellrich/Zweimüller (2013), I shed more light on the bunching behavior of firms below the threshold and investigate whether firms adjust their (nondisabled) employment in the face of the threshold. As labor costs increase at the threshold, firms just below the threshold may avoid crossing it. This may be done, for example, by extending the number of hours worked per employee or substituting workers who are counted toward the threshold number of employees with workers who are not counted (e.g., marginally employed workers). While Lalive/Wuellrich/Zweimüller (2013) find that firms below and above the threshold are quite similar in the Austrian case, my results for the German case suggest considerable differences between those firms with regard to firm dynamics, workforce and productivity. I further systematize the potential bunching of firms along the costs these firms face at the threshold. In so doing, I differentiate between *noncompliers*, which face the highest costs at the threshold, *perfect compliers*, which face lower costs at the threshold than *noncompliers*, and *overcompliers*, which do not face any additional costs at the threshold. Analyzing the extent to which these different types of firms bunch helps to clarify the role of (additional) labor costs.

[1] Note that the definition of firm/establishment size in German labor law is not consistent with that used in the German disabled worker law. Depending on the law, the (i) reference point (e.g., establishment, firm or employer), (ii) focal employee group (e.g., freelancers, marginally employed workers or apprentices) and (iii) measure of the number of employees (e.g., per capita or full-time equivalents) differ considerably.

As a preview of my results, I find that firms above the threshold do in fact employ more disabled workers than firms below the threshold. Furthermore, I find clear evidence of firms bunching just below the threshold. Firms purposely stay below the threshold and adjust their workforce accordingly to avoid the (increase in the) noncompliance fine. This bunching is particularly pronounced among *noncompliers*, i.e., those firms that face the largest increase in costs at the threshold. Taking this bunching into account, I assess the bias in the threshold effect and find that even though firms manipulate their employment, the lower bound on the threshold effect is still positive.

The remainder of the paper is structured as follows: Section 2 describes the German institutional setting, and Section 3 discusses the theoretical framework developed by Lalive/Wuellrich/Zweimüller (2013) for the German context. Section 4 presents the data set and the empirical strategy. Section 5 provides the empirical results for the intended and unintended effects, and Section 6 concludes.

2 The German Institutional Background

2.1 The Situation for Disabled Workers

In Germany, a special independent institution (*Versorgungsamt*) grants disability status once a medical expert diagnoses a physical, mental or psychological disorder that is not typical for the age of the patient. This disorder needs to be expected to last longer than six months and needs to impair the ability of the individual to participate in social life. Depending on the extent of the impairment, the medical expert evaluates the degree of the disability ranging from 20 to 100, graduated in steps of ten. An individual is defined as "severely disabled" if his or her degree of disability is greater than or equal to 50.[2] In the labor market, individuals with a degree of disability between 30 and 50 can be treated as severely disabled when their disability restricts their opportunities to find or hold a job. The decision to obtain disability status and to report that status to an employer is voluntary.

In 2011, approximately 7.3 million individuals (8.9 per cent of the total population) in Germany were considered severely disabled. Since then, the number has continued to increase to over 7.9 million in 2019 (9.5 percent). Data from the Federal Statistical Office

[2] An example of a disability of degree 50 is voicelessness or a lip-jaw cleft until closure of the jaw cleft.

from 2011 show that disabilities occur mainly in older people. A total of 53.4 percent of severely disabled individuals in Germany in 2011 were 65 years or older. The vast majority of disabilities – approximately 85 percent – are caused by illness. Hence, only a small percentage of disabilities are congenital or due to war injuries, accidents or other causes.

With regard to the degree of disability, almost a quarter (24.3 percent) of severely disabled individuals were assigned the highest degree of disability (100) in 2011, while 31.4 percent had a degree of disability of 50. Physical causes – in particular organ disorders – account for the majority of disabilities (approximately 62.3 percent). A total of 11.1 percent of disabled individuals had mental or emotional disabilities, and 9.0 percent suffered from cerebral disorders. For the remaining fraction (17.6 percent), the type of the most severe disability is not indicated (Federal Statistical Office, 2013).

2.2 The German Disabled Worker Law

The legal framework for promoting the integration of people with disabilities in the labor market in Germany is laid down in part 3 of Book IX of the Social Code, "Integration and Rehabilitation of Disabled People (SGB IX, 2001)", also called the disabled worker law (*Schwerbehindertenrecht*). Enacted in 2001, it built upon the People with Severe Disabilities Act (PSDA), which was originally implemented in 1974. In 2018, the *Bundesteilhabegesetz* replaced the former law.[3] One key element of the disability law is the *employment obligation* for public and private employers to fill at least 5 percent of their positions with severely disabled workers. Many other OECD countries, such as Austria, France, Italy and Spain, use similar quota systems to enforce the employment of workers with severe disabilities (OECD, 2003, 2010).

Key to my analysis is the fact that the quota system applies only to employers exceeding a stipulated size.[4] Small firms with fewer than 20 (nondisabled and disabled) employees are exempt from the employment obligation.[5] Firms with 20 to less than 40 employees must employ at least one severely disabled individual, whereas firms with 40 to less than 60 employees must employ at least two disabled individuals. Firms with 60 or more employees must meet the 5 percent quota. Firms that do not comply with this obligation must pay a

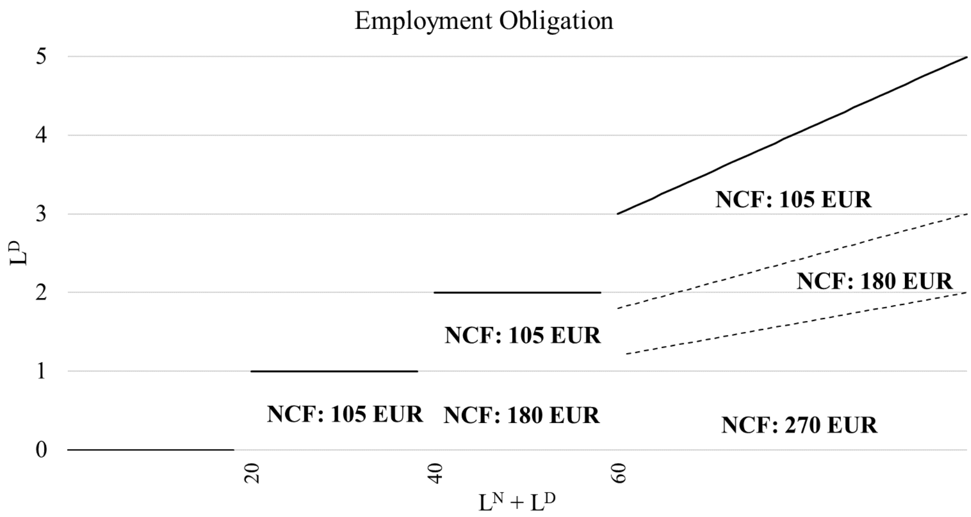
[3] Between 2001 and 2018, some marginal changes were made to the law. These changes include, for example, the role of the Federal Employment Agency in integrating disabled individuals into the labor market. However, these changes do not relate to the employment obligation or the noncompliance fine and therefore should not affect the empirical analysis.

[4] "Employers" can be natural persons or legal entities under public or private law. To measure employer size, all employees of the same employer are counted together, regardless the number of establishments or other workplaces across which they are distributed (see also Koller/Schnabel/Wagner, 2006). Thus, in the following, "employer" is used synonymously with "firm".

[5] The German regulation refers to total employment in a firm, including disabled and nondisabled workers. In contrast, the Austrian quota, for example, refers only to the nondisabled workers.

graduated noncompliance fine (*Ausgleichsabgabe*).[6] Figure 1 provides an overview of the German quota regulation and the corresponding noncompliance fines. The purpose of this noncompliance fine is to compensate firms that fulfil the employment obligation for costs incurred.[7] Such costs may arise, for example, from the need to purchase special workplace equipment for the disabled worker. Further costs may arise as employees with a recognized status "severely disabled" status are institutionally better protected in two ways. First, they are subject to special dismissal protection. If the employee has been working longer than six months in a firm, the employer needs to obtain permission for a dismissal from the local integration office. Second, a severely disabled worker receives more vacation days, i.e., an additional five days per year.

Figure 1: Employment Obligation and Monthly Noncompliance Fines in Germany



Notes: The figure shows the legal regulations concerning the German employment quota and noncompliance fines (NCF) according to § 159 SGB IX during the observation period (2004–2011). L^D is the number of workers with disabilities that firms are obligated to employ; $L^N + L^D$ represents the number of employees in a firm (i.e., firm size). For details on the firm size calculation, see Table A.1 in the Appendix. The noncompliance fines increased in 2012, 2016 and 2021. The current fines are 140, 245 and 360 EUR/month, respectively.
Source: Own illustration.

As in almost all countries with a quota system, the employment quota is generally not met in Germany. In 2011, 60.1 percent of employers with 20 or more employees did not fulfill the employment obligation and thus had to pay the noncompliance fine. Furthermore, approximately one quarter (26.2 percent) did not employ any severely disabled workers. These percentages have remaind essentially unchanged since then. In general, public

[6] Note that paying the noncompliance fine does not remove the employment obligation. Thus, employers can be fined up to 10,000 EUR in addition to the noncompliance fine if they culpably fail to comply with the employment obligation (§ 238 SGB IX). However, these fines are rarely imposed. For example, in 2010, only two fines were imposed (German Bundestag, 2011).

[7] The fine must be paid to the integration offices and is used mainly to finance assistance for occupational rehabilitation for severely disabled individuals. In 2019, the revenue from the noncompliance fine in Germany amounted to almost 696 mil. EUR (Bundesarbeitsgemeinschaft der Integrationsämter und Hauptfürsorgestellen, 2020).

employers are better at fulfilling their quotas. The share of workers with a disability is particularly low in the hotel and restaurant industry and in the agricultural sector (Federal Employment Agency, 2014).

3 Theoretical Considerations

This section mainly discusses the behavioral framework developed by Lalive/Wuellrich/Zweimüller (2013). The basic idea behind this framework is that a threshold determining the quota for workers with disabilities may affect the demand not only for disabled workers but also for nondisabled workers. In what follows, I reformulate this framework for the German quota system. This framework serves to explain the bunching behavior of firms below the quota threshold T, where T refers to the total number of workers in the firm. To examine this behavior, I look at firms with $T-1$ employees and their decision to hire an additional (disabled or nondisabled) worker.[8]

3.1 Employment Decisions at the Quota Thresholds

Lalive/Wuellrich/Zweimüller (2013) assume that nondisabled workers have productivity P, whereas disabled workers have productivity p which is less than P.[9] Because of antidiscrimination legislation, both disabled and nondisabled workers receive the same wage w.[10] The productivity of nondisabled workers exceeds the wage ($P > w$) in all firms, but firms differ in the value of p that obtains, i.e. $p < w$ in some firms and $p > w$ in other firms.[11] As the quota rule is based on a head count, labor L is assumed to be indivisible, while product demand Z is assumed to be continuous. Labor consists of L^N nondisabled and L^D disabled workers.

[8] Note that the framework presented below refers to the *first* threshold in Germany (20 employees) in order to explain the general logic behind the quota system. This logic also generalizes to higher thresholds. In subsection 3.2, I also discuss the implications of the framework for employment manipulation at the *second* threshold (40 employees).

[9] Assuming that $p < P$ is plausible in the German context: Survey results show that a considerable share of German establishments report a lower level of performance and resilience and a higher level of absence rates among workers with disabilities than among workers without disabilities (Hiesinger/Kubis, 2022).

[10] Note that I assume that firms face the same hiring costs for disabled or nondisabled workers. But as disabled individuals may have a lower labor force participation, hiring disabled workers may result in higher search costs. These additional search costs would then increase the marginal costs of hiring disabled workers. However, for the sake of simplicity, I abstract from including these additional costs in my framework.

[11] Note that a workers' productivity within a firm may decline depending on the level of employment (see also footnote 15).

Let us first discuss this system in the *absence of a quota*. The firm's profit function can be described as

$$\pi_0(L^N, L^D) = min(PL^N + pL^D, Z) - w(L^N + L^D) \quad (1)$$

"Residual demand" is defined as the product demand Z minus the output produced by the L^N nondisabled workers:

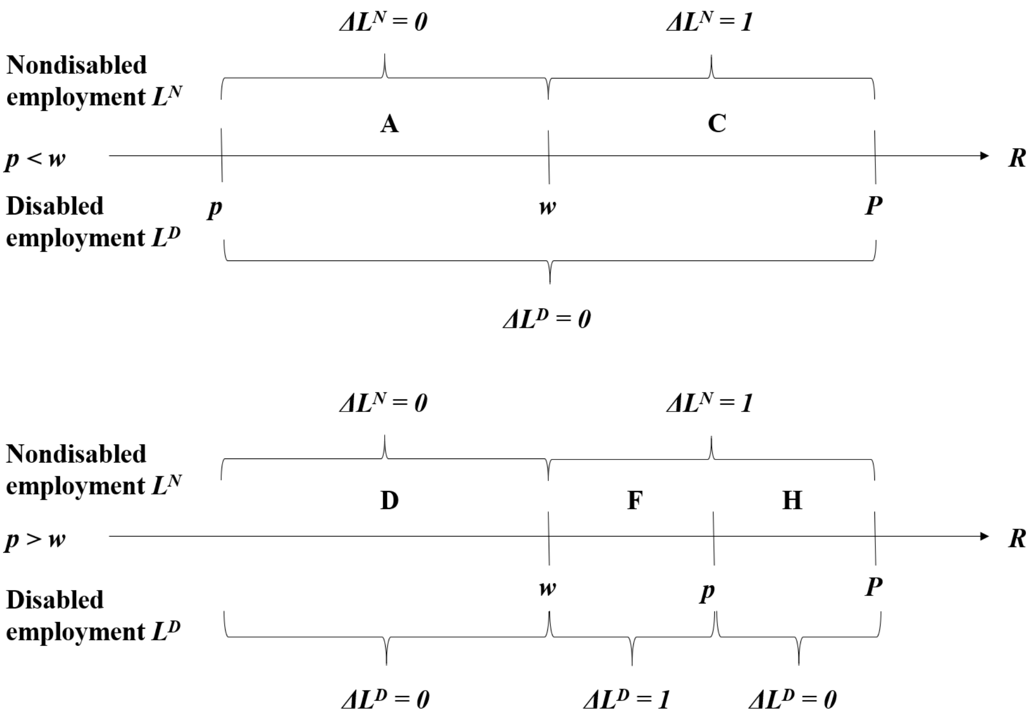
$$R(Z, L^N) = Z - L^N P \quad (2)$$

Figure 2 illustrates the firm's employment decisions in the absence of a quota for $p < w$ and $p > w$. In either case, the firm will not hire an additional nondisabled worker ($\Delta L^N = 0$) as long as residual demand is below the wage rate: $R(Z, L^N) < w$ (*A*- and *D-firms*). When residual demand exceeds the wage rate ($R(Z, L^N) > w$), the firm will hire an additional nondisabled worker ($\Delta L^N = 1$) (*C-firms*). However, the firm is not willing to hire a disabled worker ($\Delta L^D = 0$) as long as $p < w$: The productivity of the disabled worker is always too low to satisfy the residual demand. When $p > w$ and residual demand is in the range $R(Z, L^N) \in (w, p)$, the firm is indifferent between hiring a disabled or a nondisabled worker, as the productivity of both workers is great enough to satisfy the residual demand (*F-firms*). A firm with large residual demand $p < R(Z, L^N) < P$ will strictly prefer hiring a nondisabled worker over a disabled worker (*H-firms*).

Now let us describe a system in the *presence of a quota*. In Germany, firms with total employment below the threshold T (i.e., $L^N + L^D < T$) do not face an employment obligation for disabled workers, whereas firms with total employment at or above T (i.e., $L^N + L^D \geq T$) need to employ at least one disabled worker. Note that the German system differs from the Austrian system presented in Lalive/Wuellrich/Zweimüller (2013). Specifically, the quota in Germany is determined on the basis of total employment, i.e., nondisabled *and* disabled employment ($L^N + L^D$), whereas the quota system in Austria is based only on nondisabled (L^N) employment. Firms must pay a noncompliance fine τ if they do not satisfy their employment obligation. Following Lalive/Wuellrich/Zweimüller (2013), I assume that $\tau < w$ and $\tau < P - p$.[12] The profit function in the presence of a quota given nondisabled employment L^N and disabled employment $L^D \in \{0, 1\}$ can be

[12] Both assumptions are plausible in the German context. First, among firms with 20-60 employees, the noncompliance fine is only approximately 4.3-7.5% of gross monthly earnings. Second, the degree of disability (see Section 2.1) reflects the extent of the impairment caused by the disability. For severely disabled workers (those with a degree of disability of at least 50), it is plausible to assume that this impairment substantially affects their labor productivity. Furthermore, survey results show that a considerable share of German establishments report that workers with disabilities have a lower level of performance and resilience and a higher rate of absence than workers without disabilities (Hiesinger/Kubis, 2022).

Figure 2: No Quota



Notes: The figure shows the employment decisions of firms with $T-1$ employees in the absence of a quota system.
Source: Own illustration based on the discussion in Lalive/Wuellrich/Zweimüller (2013).

described as

$$\begin{aligned}\pi_1(L^N, L^D) = &\, min(PL^N + pL^D, Z) - w(L^N + L^D) \\ &+ min[L^D - 1(L^N + L^D \geq T), 0] \cdot \tau \end{aligned} \tag{3}$$

$$\text{with } (L^N + L^D \geq T) = \begin{cases} 1 & \text{if } L^N + L^D \geq T \\ 0 & \text{if } L^N + L^D < T \end{cases}$$

For employment decisions in the presence of a quota, I again distinguish between the cases $p < w$ and $p > w$, as shown in Figure 3. When $p < w$, firms will not hire any disabled workers, even in the presence of a quota ($\Delta L^D = 0$). However, the quota may affect nondisabled employment. A firm with residual demand R in the range $(w, w + \tau)$ will not hire an additional nondisabled worker ($\Delta L^N = 0$), whereas it would have hired that worker in the absence of the quota (see Figure 2). The marginal cost an additional nondisabled worker is now the wage w of this worker *plus* the tax τ. In the range $(w, w + \tau)$, this marginal cost is larger than the residual demand. Thus, firms with residual demand in this range, i.e., *B-Firms*, are better off setting their employment level just below the threshold, i.e.,

$L^N + L^D = T - 1$, to avoid the tax. Avoiding the tax by staying below the threshold – i.e., *bunching* – is the *unintended effect* of the quota.

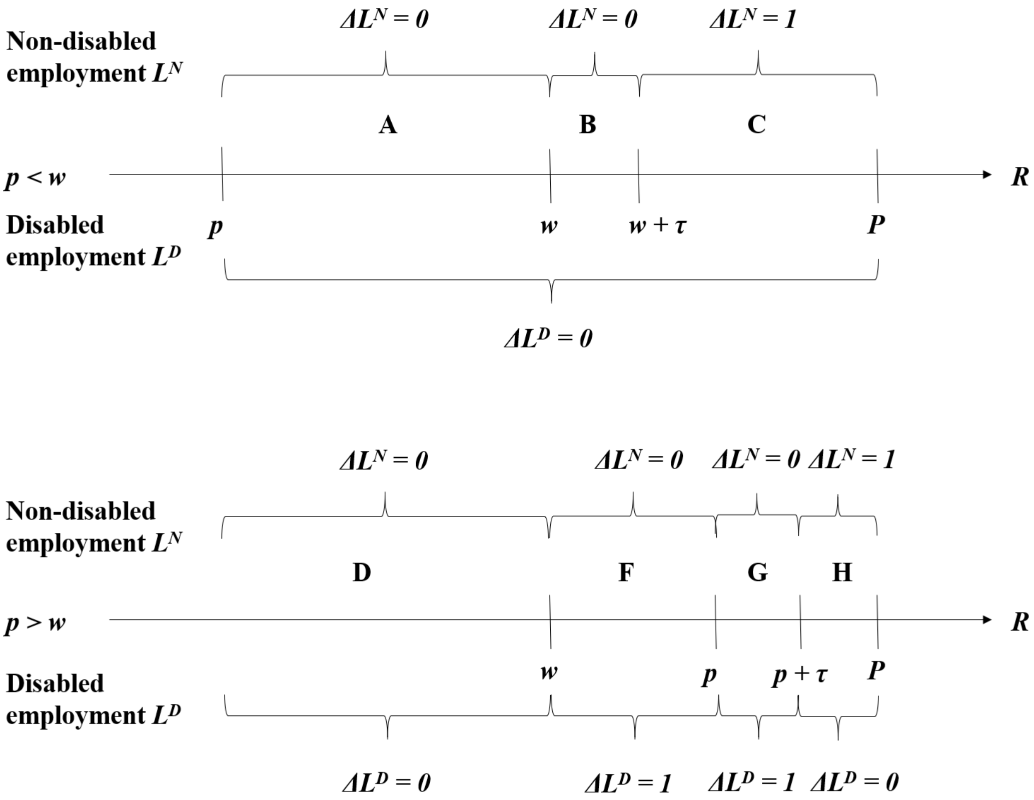
For $p > w$, the decision to hire a disabled worker depends on the residual demand R. The quota rule does not affect *D-firms*, which have a low level of residual demand in the range $(0, w)$. As residual demand does not exceed the wage rate, an additional worker – disabled or not – would not produce the needed revenue. However, firms with residual demand in the range (w, p), *F-firms*, and in the range $(p, p + \tau)$, *G-firms*, now prefer to hire a disabled worker instead of a nondisabled worker as they would have to pay the (additional) fine when hiring a nondisabled worker (without a quota, *F-firms* are indifferent between hiring a disabled or a nondisabled worker while *G-firms* prefer to hire a nondisabled worker and no disabled workers). Incentivizing firms to hire a disabled worker instead of a nondisabled worker is the aim of the quota and thus reflects its *intended effect*. *H-firms*, with residual demand in the range $(p + \tau, P)$, prefer hiring a nondisabled worker, as this worker generates higher profits despite the fine.[13]

Let us now have a closer look at manipulating firms. Lalive/Wuellrich/Zweimüller (2013) define *manipulators* as firms that set their employment level below the threshold under the quota system but above it without such a system. The Austrian system induces *B-firms* and *G-firms* to manipulate employment, as the Austrian quota is defined on the basis of nondisabled employment. *B-firms* do not hire a disabled worker and set their nondisabled employment level below the threshold to avoid the tax. *G-firms* also set their nondisabled employment level below the threshold but hire a disabled worker (because he or she increases profit). In the Austrian system, *G-firms* that hire a disabled worker are still located *below* the threshold. However, in contrast to the Austrian system, the German system induces only *B-firms* to manipulate their employment. As the German quota is based on total – i.e., nondisabled and disabled – employment, *G-firms* cross the threshold when they hire a disabled worker and are located *above* the threshold. Thus, I expect potential manipulation to arise entirely from *B-firms*, for which $p < w$ and which purposely stay below the threshold to avoid the fine.

How does this manipulation bias the difference in the average number of disabled workers between firms with $T - 1$ employees and firms with T employees? Due to the quota, the composition of firms with $T - 1$ employees changes: *B-firms* would have hired an additional nondisabled worker without the quota (i.e., they would have chosen employment level T) but now bunch below the threshold in the presence of the quota. As *B-firms* are not willing

[13] Lalive/Wuellrich/Zweimüller (2013) also discuss employment decisions for firms at or above the threshold T (where T refers to the number of nondisabled workers), i.e., the decision to hire T or $T + 1$ workers. Those firms will hire an additional disabled worker when the residual demand is in the range $(w - \tau, w)$, as the marginal cost of hiring a disabled worker is $w - \tau$ and thus less than the residual demand. As I focus on employment decisions *below* the threshold, i.e., the decision to hire $T - 1$ or T workers, I do not discuss this case in more detail.

Figure 3: Quota



Notes: The figure shows the employment decisions of firms with $T-1$ employees in the presence of a quota system.
Source: Own illustration based on the discussion in Lalive/Wuellrich/Zweimüller (2013).

to hire an additional disabled worker, the difference in the average number of disabled workers between firms below and at the threshold is *overestimated*.

Manipulating firms may further adjust their employment (Koller/Schnabel/Wagner, 2006): To avoid crossing the threshold, *B-firms* may extend the number of hours worked for (incumbent) employees. Note that forcing workers to work overtime could be costly due to overtime pay. However, a firm may, for example, substitute part-time workers with full-time workers. A second option includes substituting workers who are counted when determining whether the firm is subject to the quota (e.g., regularly employed workers) with workers who are not so counted (e.g., marginally employed workers). Note that this would only be the case when the productivity of the members of these working groups is sufficient to meet the product demand. In sum, bunching may lead to different wage and employment structures in a firm.

3.2 Manipulation of Employment at the Second Threshold

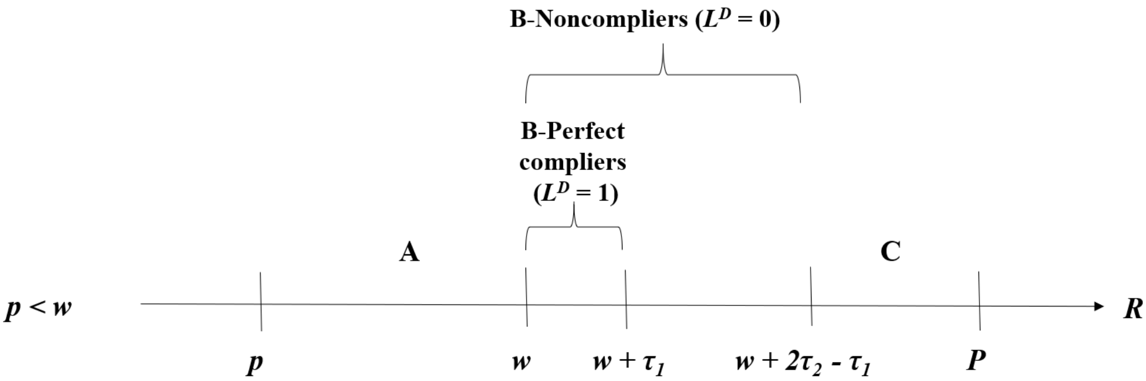
As my empirical analysis focuses on the second threshold of 40 employees, let us now briefly discuss the marginal cost for firms with employment just below this *second* threshold (i.e., $L^N + L^D = T_2 - 1$). As shown in Figure 1, the German labor law defines two levels of the fine depending on the *initial* level of disabled employment around the second threshold (τ_1 and τ_2 with $\tau_2 > \tau_1$).[14] Thus, there are three types of firms with $L^N + L^D = T_2 - 1$ employees: First, firms with an initial level of disabled employment $L^D = 0$ already pay the noncompliance fine τ_1. When crossing the threshold, the noncompliance fine increases to $2 \cdot \tau_2 - \tau_1$, provided that it is not the hiring of disabled worker that causes the firms to cross the threshold. I refer to these firms as *noncompliers*. Second, firms with an initial level of disabled employment $L^D = 1$ are in perfect compliance with the quota rule. When crossing the threshold, these firms would be obliged to pay the noncompliance fine τ_1, again provided that they do not hire another disabled worker. I refer to these firms as *perfect compliers*. In the German context during the observation period, *perfect compliers* (*noncompliers*) face additional costs of 1260 EUR/year (3060 EUR/year) at the threshold. Finally, firms with $L^D \geq 2$ already employ more disabled workers than required by law. These firms do not face any additional costs at the threshold, as they do not have to pay a noncompliance fine regardless of whether they are below or above T_2. I refer to these firms as *overcompliers*.

What are the consequences for employment manipulation at T_2? As shown in Section 3.1, employment manipulation arises entirely from *B-firms*, for which $p < w$. I identify two types of manipulating firms according to the marginal cost that they face at T_2. First, *B-noncompliers* are firms with no disabled workers and with residual demand in the range $(w, w + 2 \cdot \tau_2 - \tau_1)$. Second, *B-perfect compliers* are firms that already have one disabled worker and residual demand in the range $(w, w + \tau_1)$.[15] Since the range of bunching is larger among *B-noncompliers* as shown in Figure 4, I expect bunching to be more pronounced among this type of firm than among *B-perfect compliers*.

[14] Note that I treat the *initial* level of disabled employment as given and discuss only the decision of firms with $L^N + L^D = T_2 - 1$ employees to hire an *additional* disabled or nondisabled worker.

[15] The fact that I allow *perfect compliers* to bunch even though they have already hired one disabled worker may be rationalized by a decreasing marginal product. This assumption implies that beyond a given level of employment, the ratio of p to w may change. Thus, for some firms, the productivity of the first disabled worker exceeded the wage (i.e., $p > w$) when the firm had a lower employment level (for example, at the first threshold), while this is no longer the case at the second threshold (i.e., $p < w$).

Figure 4: Types of B-Firms at T_2



Notes: The figure shows the employment decisions of firms at the first (top panel) and the second threshold (bottom panel). *Perfect compliers* are firms with one disabled worker, and *noncompliers* are firms with no disabled workers. *A-firms* are firms that do not hire a nondisabled worker, whereas *C-firms* are firms that hire a nondisabled worker. *B-firms* are firms that would hire a nondisabled worker in the absence of a quota system but would not hire a nondisabled worker in the presence of such a system (see Figures 2 and 3).
Source: Own illustration.

4 Empirical Strategy, Data and Variables

4.1 Data

My empirical analysis is based on two administrative data sets from the German Federal Employment Agency. The *Employment Statistics for Severely Disabled People* (BsbM) is an annual set of statistics that has been available since 2003 and that includes information on the employment of disabled workers in firms. Firms with 20 or more employees must annually declare (i) how many individuals they employ and (ii) how many of them are severely disabled. Thus, the information on firm size and the number of disabled workers stems directly from the notifying procedure used to determine compliance with the disabled worker quota. As a consequence, the BsbM has the great advantage of providing information on firm size that is consistent with the legal definition stipulated in the disabled worker law.[16] Note that many studies that have analyzed regulations with a firm size criterion, e.g., in the context of dismissal protection, have tried to approximate the firm size stipulated in the respective law (see, for example, Wagner/Schnabel/Kölling, 2001; Bauer/Bender/Bonin, 2007; Bauernschuster, 2013; Hijzen/Mondauto/Scarpetta, 2017).

[16] For details on the definition of firm size according to the disabled worker law, see Table A.1 in the Appendix.

Thus, these analyses often suffer from a considerable amount of measurement error, which can be ruled out in my case. In addition to some basic information about the firm, such as region and industry, the BsbM contains an identifier for the establishment or the main establishment in the case of multiestablishment firms.

This identifier allows me to merge additional information from the establishment data of the Federal Employment Agency, namely, the *Establishment History Panel* (BHP) (Schmucker et al., 2018). Since I consider only small businesses with up to a maximum of 80 employees, I can assume that in most cases, each firm consists of one establishment.[17] This allows me to merge the firm data with the establishment data. The Establishment History Panel provides annual detailed information on each establishment's workforce, such as its skill or employment structure, as of the reference date, June 30th.

4.2 Empirical Strategy

The employment obligation for firms, which varies according to the firm size thresholds, provides a natural application for a "threshold design" (Lalive/Wuellrich/Zweimüller, 2013).[18] I use the second threshold and compare the various outcome variables, most importantly the number of workers with disabilities, of firms just below and just above the threshold of 40 employees.[19] The key assumption for identifying the effect of the quota is that firm demand for disabled workers would be continuous in the absence of the employment obligation. This assumption is reasonable, as no rules – other than the disabled worker quota – take effect when firms change their employment levels around the thresholds. However, as the noncompliance costs rise sharply at the thresholds, firms may

[17] According to the establishment panel, a representative survey of establishments in Germany, a large majority of establishments are independent companies without any other places of business. This is particularly true for small establishments, thus minimizing the error from treating establishments as single firms. For details, see Figure A.1 in the Appendix. In the case of multiestablishment firms, the establishment information in the *Establishment History Panel* (i.e., the information on the employment, wage and skill structures) refers only to the main establishment. Thus, for multiestablishment firms, the "bunching behavior" analyses (see Section 5.5) would be biased if the wage, skill and employment structures in the main establishment differs substantially from the wage, skill and employment structures in the branch offices. As a robustness check, I exclude those firms that I can identify as multiestablishment firms. For more details, see Section 5.6.1.

[18] Although closely related to an RDD, the threshold design has a slightly different setup than the RDD, as the running variable – firm size in my case – is an endogenous variable. The estimation techniques are, however, very similar.

[19] Due to data limitations, I cannot exploit the first threshold of 20 employees, as the BsbM data set covers only firms affected by the employment obligation, i.e., firms with 20 or more employees. Furthermore, I do not focus on the third threshold of 60 employees for two reasons. First, the assumption that a firm consists of only one establishment (see Section 4.1) is more plausible for smaller firms. Second, there are additional labor law rules with thresholds (apart from the disabled worker quota) for firms with at least 60 employees (see Section 5.8). Thus, I cannot ensure that the effects that I find for this threshold are due solely to the disabled worker quota.

indeed choose to manipulate their employment levels in the presence of the disabled worker quota and purposely stay below the threshold to avoid this additional fine.

Therefore, following Lalive/Wuellrich/Zweimüller (2013), my empirical analysis consists of two parts. First, I estimate the intended threshold effect, which is the (naive) effect of the threshold regulation on the number of disabled workers. Second, I report the unintended bunching effect, which is the effect of the threshold regulation on firm size. The bunching effect thus indicates the maximum number of firms at the threshold that manipulate their size. Taking this potential bunching effect into account, I am able to bound the threshold effect.

To estimate the *threshold effect*, I rely on graphical analyses to provide initial intuition. For this, I plot the local averages of the number of disabled employees per firm size category. In my case, the firm size categories are defined by the whole numbers of employees in a firm. I complement this nonparametric analysis with weighted local polynomial regressions using the following equation:

$$\begin{aligned} Y_i = &\beta_0 + D_i\,\beta_1 + (1-D_i)\,c_i\,\beta_2^- + D_i\,c_i\,\beta_2^+ \\ &+ (1-D_i)\,x_i\,\beta_3^- + D_i\,x_i\,\beta_3^+ + \epsilon_i, \end{aligned} \tag{4}$$

where Y_i is the outcome variable, i.e., the number of disabled workers in firm i. D_i is a treatment dummy indicating whether the firm is above the critical threshold of 40 employees and thus obliged to employ one additional severely disabled worker according to the law. c_i is the running variable that the cutoff is based on (firm size).[20] Both c_i and x_i are defined as deviations from the treatment cutoff, i.e., $c_i = C_i - C$, $x_i = X_i - C$, where C denotes the cutoff and X_i represents a vector of control variables capturing predetermined observable firm characteristics.[21] Including these predetermined characteristics helps to reduce the sampling variability in the estimator. The superscripts '$-$' and '$+$' indicate whether the coefficient relates to the left- or right-hand side of the threshold. ϵ_i represents the error term. All coefficient estimates are obtained from a local linear regression that weights all observations by their deviations from the cutoff using a triangular kernel.[22]

The aim of the analysis is to extrapolate the counterfactual number of disabled workers in firms at the threshold in the absence of the noncompliance fine. Equation 4 assumes a linear functional form (with polynomial order p=1), which can be misspecified. Thus, to assess the sensitivity of estimates to the functional form, I add higher-order polynomials to

[20] Note that this running variable is discrete and takes on 40 distinct values (mass points) between 20 and 59 employees. However, as the number of observations per mass point is sufficiently large (approximately 7,000-30,000 observations per mass point), I can apply the continuity approach presented above (Cattaneo/Irobo/Titiunik, 2018).
[21] In my case, C_i refers to the whole number of (disabled and nondisabled) employees in firm i.
[22] This weight is optimal in the MSE-optimal context (Cattaneo/Idrobo/Titiunik, 2019).

the linear model. In so doing, I additionally use polynomials with respect to the running variable of order 2, 3 and 4. Regarding the bandwidth – the window of relevant observations around the threshold – I choose a mean square error optimal (MSE-optimal) bandwidth for each side of the threshold (Calonico/Cattaneo/Farrell, 2020; Cattaneo/Vazquez-Bare, 2016).[23] Furthermore, as I use pooled cross-sectional firm data, I display standard errors adjusted for clustering at the firm level.[24]

To estimate the unbiased effect of the threshold on the number of disabled workers in the firm, I have to assume that firms do not manipulate their firm size in order to purposely stay below the threshold. However, as (noncomplying) firms face an increase in labor costs at the threshold due to the increased noncompliance fine, this assumption may possibly be violated (see Section 3). Thus, I explicitly address the question of how the manipulation of employment level may bias the estimated naive threshold effect. To do so, I first check whether manipulation is present by graphically inspecting firm size density. The intuition behind this test is that bunching should be reflected as a discontinuity in the firm size distribution at the threshold (see McCrary, 2008). Due to the increased labor costs at the threshold, I expect a negative discontinuity in firm size density at the threshold. I also formally check for the presence of bunching (Cattaneo/Jannson/Ma, 2020). Furthermore, again following Lalive/Wuellrich/Zweimüller (2013), I quantify the effect on the firm size density – the *bunching effect* – to assess the bias in the estimated naive threshold effect. For this, I use an equation similar to equation (1) but with firm size density (in percentage terms) as the outcome variable. Again, I estimate different specifications, including specifications with different polynomial orders.

To shed additional light on the bunching behavior of firms, I further inspect alternative outcome variables by replacing the dependent variable in equation 4 with each of the alternative outcome variables. These variables include information on firm workforce composition, firm productivity and firm dynamics. Firms just below the threshold that

[23] The form of the MSE-optimal bandwidth is $h_{MSE} = C_{MSE} \cdot n^{-1/(2p+3)}$ (Cattaneo/Vazquez-Bare, 2016). n indicates the sample size available, and p indicates the polynomial order. The constant C_{MSE} involves several known and unknown values that depend on objects such as the kernel function, the parameter of interest, p, the asymptotic bias and variance of the estimator, and whether additional predetermined covariates are included in the estimation. h_{MSE} is constructed by forming a preliminary estimator $\hat{C}_{MSE}$ of the unknown constant C_{MSE}, which leads to the estimated bandwidth $\hat{h}_{MSE} = \hat{C}_{MSE} \cdot n^{-1/2p+3}$. Thus, the selected bandwidth around the threshold T takes the form $[T - \hat{h}_{MSE}, T + \hat{h}_{MSE}]$. As a consequence, only observations within this bandwidth are used. This estimator is data-driven and objective. Note, however, that one cannot directly use the MSE-optimal point estimator for inference. The bandwidth $[T - \hat{h}_{MSE}, T + \hat{h}_{MSE}]$ is selected for MSE-optimal point estimation. Thus, bias and variance are balanced in a manner that makes inference invalid by construction when the same observations and estimator are used. Calonico/Cattaneo/Titiunik (2014) propose an inference approach based on bias correction for the point estimate. Hence, the *robust* confidence intervals are fully compatible with the use of the observations in the selected MSE-optimal bandwidth and are still valid (Cattaneo/Vazquez-Bare, 2016).

[24] Furthermore, following the guide for multiway clustering by Cameron/Miller (2015), I provide standard errors clustered at the firm level *and* at the discrete values of the running variable (firm size) for my main specification in column (5) of Table 2. To do so, I calculate the standard errors using the following equation: $se_{twoway} = \sqrt{se_1^2 + se_2^2 - se_{1\cap 2}^2}$ (see the notes to Table 2).

manipulate their employment levels may substitute regular (full-time) employed workers with workers whose employment does not count toward their firms size for purposes of the quota, such as marginally employed, part-time workers ($<$18 hours/week) or apprentices. Such substitution effects would be reflected in differences in the workforce composition and in firm productivity below and above the threshold. Another alternative outcome variable is employment growth, as manipulating firms may have lower employment growth just below the threshold.[25] As I expect different bunching behavior among different types of firms below the threshold, I always distinguish between *noncompliers*, *perfect compliers* and *overcompliers* (see Section 3).

In summary, my empirical approach explicitly takes potential violations of the key assumptions of a standard RDD/threshold design into account. Specifically, my approach accounts for the fact that observations just below and just above the threshold may indeed be different with regard to workforce composition, productivity and dynamics. However, with regard to *predetermined covariates* such as region, industry and firm age, the observations below and above the threshold should not differ substantially. I first report on these predetermined covariates for firms located around the threshold of 40 employees and formally check for discontinuities at the threshold. Again, I replace the dependent variable in equation 4 with each of the predetermined covariates (see columns (4) and (5) of Table 1). Testing for local balance in the predetermined covariates is important to ensure that firms just below the threshold represent an appropriate control group for treated firms just above the threshold. Furthermore, I include those predetermined covariates as control variables in my main estimations.

4.3 Sample and Descriptive Statistics

As described earlier, I focus on the second threshold of 40 employees in my main analysis. My baseline sample consists of firms with 29 to 51 employees (according to the BsbM) in the years 2004 to 2011, resulting in 319,939 firm-year observations.[26]

Table 1 reports predetermined firm characteristics (firm age, region and industry) for firms around the threshold of 40 employees. By construction, firms above the threshold have more employees than control firms and are, on average, older. Firms below and above the threshold also differ with regard to their industrial and geographical distribution. However, note that even though all differences are statistically significant at the 1 percent level, most

[25] I define employment growth with a dummy variable equal to 1 if a firm has more employees (according to the BsbM) in $t+1$ than in t and equal to 0 otherwise.

[26] Note that restricting the sample to firms with 29 to 51 employees is only relevant for describing the predetermined characteristics of the firms. In the analysis, the sample differs across the different specifications, as I calculate the MSE-optimal bandwidth for each estimation.

of them are small in size. The mean differences between firms below and above the threshold may also reflect heterogeneity in the firm size distribution across industries and regions. Thus, I formally test for discontinuities in these characteristics at the 40-employee threshold for polynomials of both order 1 and order 4 with an MSE-optimal bandwidth. Columns (4) and (5) of Table 1 report the estimated coefficients. The results for the specification with a very flexible functional form (p=4) show that there is only one statistically significant and sufficiently large coefficient (see column (5) of Table 1). In particular, the share of public administration firms is significantly different between firms below and above the threshold in general, and there is also a significant (and quite large) discontinuity exactly at the threshold. Hence, I exclude public administration firms in a robustness check to analyze whether my main results are sensitive to this exclusion. Altogether, this inspection of differences in predetermined characteristics suggests that firms below the threshold represent a basically appropriate control group for firms above the threshold.

Table 1: Descriptive Statistics for Firm Characteristics

	Below Threshold 29-39 Employees	Above Threshold 40-51 Employees	Difference	Discontinuity At 40-Employee Threshold	
	(1)	(2)	(3)	(4)	(5)
	Mean	Mean	t test	$p = 1$	$p = 4$
Firm Size	33.64	45.18	11.53***		
Age of Establishment	18.80	19.17	0.370***	0.403**	0.954*
Region: East Germany	0.171	0.171	-0.001***	-0.004	0.009
Industry Shares					
Agriculture	0.022	0.016	-0.006***	-0.000	0.003
Energy/Mining	0.009	0.012	0.003***	0.001	0.002
Manufacturing	0.245	0.270	0.025***	0.013*	0.039
Construction	0.096	0.082	-0.014***	-0.007*	-0.029
Wholesale	0.182	0.172	-0.009***	0.005	0.005
Traffic/Communication	0.066	0.062	-0.004***	-0.010***	0.024
Banking/Insurance	0.010	0.014	0.004***	0.007***	0.011*
Other Services	0.188	0.175	-0.013***	-0.021**	-0.021
Public Administration	0.137	0.158	0.021***	0.022***	0.037**
Public Sector	0.045	0.039	-0.005***	-0.002	-0.009
# of Firm-Year Observations	202,583	117,356	319,939		

Notes: The table presents descriptive statistics for the characteristics of firms around the 40-employee threshold. p indicates the order of the polynomial in the specification. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels. The standard errors for the estimates in columns (4) and (5) are clustered at the firm level.
Source: BsbM and BHP 2004–2011, own calculations.

5 Results: Intended and Unintended Effects

5.1 Demand for Disabled: Graphical Illustration

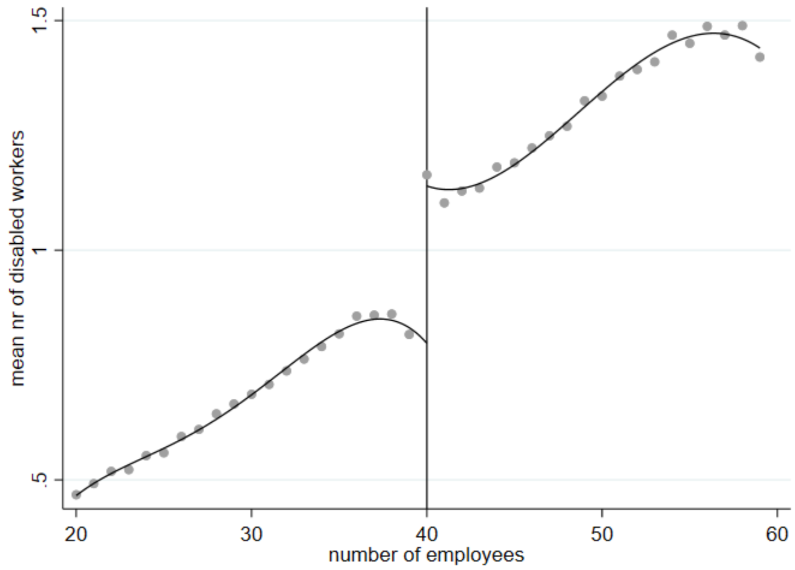
Let us now turn to the graphical illustration of a potential discontinuity at the second threshold of 40 employees. Figure 5 displays the mean number of disabled workers by firm size for the threshold of 40 employees. It shows that the number of disabled workers employed by firms increases with firm size in a quite linear fashion. Firms at the bottom of the observed firm size distribution, i.e., firms with 20 employees, employ on average 0.47 disabled workers, whereas firms at the top of the observed firm size distribution, i.e., firms with 59 employees, employ on average 1.42 disabled workers. The plot shows a considerable discontinuity in the number of disabled workers at the threshold. While firms just below the threshold, i.e., firms with 39 employees, employ on average 0.817 disabled workers, firms just above the threshold, i.e., firms with 40 employees, employ 1.164 disabled workers.

However, the figure also illustrates that the (linear) increase in the number of workers with disabilities slows and eventually reverses into a decline just before the threshold, which can be interpreted as a first indication of bunching behavior: those firms that do not employ enough workers with disabilities may purposely stay below the threshold.

5.2 Demand for Disabled: Naive Effects

Table 2 reports the econometric results for the estimated (naive) threshold effects. I estimate five models with different bandwidths and polynomial orders. The first model in column (1) shows the results for the basic econometric model with an MSE-optimal bandwidth on either side of the threshold, a linear functional form, and predetermined firm characteristics included as control variables. The estimated discontinuity at the threshold is 0.345. This discontinuity is significantly different from zero at the 1 percent level. Columns (2), (3) and (4) use higher-order polynomials and again estimate the optimal bandwidth below and above the threshold. The results show that the estimates are sensitive to functional form. Higher-order polynomials lead to larger threshold effects. This is not surprising, as a more flexible functional form takes the (nonlinear) developments near the threshold into account (see Figure 5). Column (5) also uses a very flexible functional form but with a fixed bandwidth of $h_{below} = 8$ and $h_{above} = 9$ based on the optimal bandwidth in

Figure 5: Number of Disabled Workers



Note: This graph plots the average number of disabled workers by firm size around the 40-employee threshold. The black line approximates the functional form of the running variable (here with polynomial order $p = 4$ and bandwidth $h_{below} = 20$ and $h_{above} = 19$).
Source: BsbM and BHP 2004–2011, own calculations.

column (4).[27] The estimated coefficients in column (4) and column (5) are very similar. I therefore adopt the model in column (5) with a threshold effect of 0.388 as my *baseline specification* for the remainder of the analysis.

In quantifying the magnitude of the naive effect, the estimates suggest that the employment obligation leads to threshold firms employing 0.388 more disabled workers. Given that the mean number of disabled workers just below the threshold is 0.817, this effect represents an increase in the number of disabled workers of 47 percent. This effect is considerably larger than the 12 percent effect that Lalive/Wuellrich/Zweimüller (2013) found in their analysis of the Austrian case. However, Lalive/Wuellrich/Zweimüller (2013) also found relatively small bunching effects. Given the visual hints in this section that bunching may be a more salient issue in the German case, the large threshold effect found in this naive analysis may be upwardly biased (see Section 3.1). Therefore, I shed additional light on potential bunching effects and bunching behavior in the following section.

[27] For the choice of bandwidth in this specification, I use the estimated optimal bandwidths in column (4) as my benchmark and round up to the nearest whole number. Thus, I gain predefined and uniform bandwidths that I can use to calculate the bunching effects. Uniform bandwidths that encompass a fixed number of firms are important for calculating the lower bound on the threshold effect (see Section 5.4).

Table 2: Threshold Effects (Dep. Var.: Number of Disabled Workers)

	40-Employee Threshold				
	(1)	(2)	(3)	(4)	(5)
Effect (β_1)	0.345***	0.373***	0.386***	0.394***	0.388***
Robust CI (1)	[0.318; 0.429]	[0.318; 0.456]	[0.320; 0.469]	[0.304; 0.492]	[0.185; 0.668]
Bandwidth h	2.20; 3.38	4.15; 5.51	6.54; 7.58	8.31; 9.46	8; 9
Polynomial Order p	1	2	3	4	4
Covariates Included	yes	yes	yes	yes	yes
# of Observations	76,271	129,228	182,727	238,306	210,306

Notes: This table presents the estimation results for the effect of the threshold on the number of disabled workers in a firm (threshold = firm size of 40 employees). Basic covariates include firm age, regional characteristics (federal state) and industry. The bandwidths in columns (1)-(4) reflect the MSE-optimal bandwidths calculated with the *rdrobust* command in Stata. As the running variable (firm size) is discrete, estimates are adjusted for mass points in the running variable. Standard errors are clustered at the firm level. The robust confidence interval for the main specification in column (5) with standard errors clustered at the firm level and discrete values for the running variable (firm size) is [0.296; 0.557]. *** denotes statistical significance at the 1% level.
Source: BsbM and BHP 2004–2011, own calculations.

5.3 Unintended Effect: Bunching Below

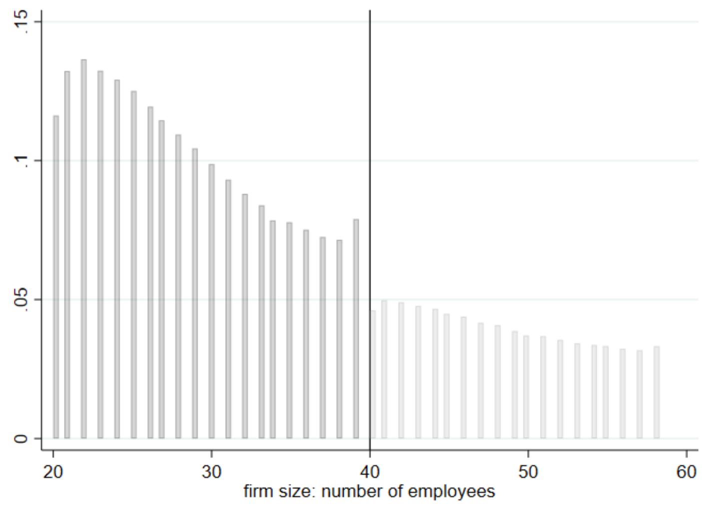
This section analyzes the potential bunching effect that results from firms purposely staying below the firm size threshold. The histogram shown in Figure 6 further indicates the importance of manipulation. It shows that firm size density drops at the threshold, indicating that manipulation may indeed be an issue. I also formally test for the presence of a discontinuity in the firm size distribution (Cattaneo/Jannson/Ma, 2020). The test results suggest that the null that there is no bunching should be rejected at the 1 percent level (see Table B.1 and Table B.2 in the Appendix).[28] To quantify the extent of the bunching, I calculate the share of firms in each firm size category and run local regressions around the threshold with the calculated firm size density as the outcome variable. I again use different polynomial orders (2, 3 and 4) to check whether the results are sensitive to functional form.[29]

Table 3 shows the results from estimating the bunching effects. The coefficient from the model with a second-order polynomial is -1.305. The models incorporating a more flexible functional form suggest larger bunching effects. When using a very flexible functional form, i.e., with a polynomial of order 4 and a fixed bandwidth of h_{below}=8 and h_{above}=9 based on my baseline specification in Section 5.2, the bunching effect is -2.017. This means that approximately 2 percent of the firms around the threshold have manipulated their size.

[28] I also perform the manipulation test proposed by Frandsen (2017) in the context of RDDs with a discrete running variable. This test also indicates that there is systematic manipulation of the running variable.
[29] Note that it is not possible to estimate a linear specification (p=1) with the MSE-optimal bandwidth calculation in this case due to the very small number of observations.

Taken together, the evidence suggests firms indeed seem to manipulate their size due to the (higher) noncompliance fine that is imposed for firms with 40 or more employees. This suggests that the large threshold effect on the number of disabled workers identified in Section 5.2 is upwardly biased.

Figure 6: Firm Size Density



Note: Histogram indicating firm size density around the 40-employee threshold.
Source: BsbM and BHP 2004–2011, own calculations.

Table 3: Bunching Effects (Dep. Var.: Firm Size Density)

	40-Employee Threshold			
	(1)	(2)	(3)	(4)
Bunching Effect	-1.305***	-1.454***	-2.012**	-2.017
Robust CI	[-2.198; -0.604]	[-2.587; -0.535]	[-4.080; -0.212]	[-5.521; 1.702]
Bandwidth h	6.38; 7.20	8.34; 10.07	7.96; 11.03	8; 9
Polynomial Order p	2	3	4	4
# of Observations	14	19	19	16

Notes: This table shows estimation results for the effect of the 40-employee threshold on firm size density (in %). ** and *** denote statistical significance at the 5% and 1% levels.
Source: BsbM and BHP 2004–2011, own calculations.

5.4 Bounding the Effect

This section assesses the upward bias in the naive threshold effect and provides a lower bound on the effect, again following the strategy used by Lalive/Wuellrich/Zweimüller (2013). For this, I refer to my baseline specification in which h_{below}=8, h_{above}=9 and p=4 for both the bunching and the threshold effects. The bunching effect of -2.017 identified in

Section 5.3 informs us about the absolute number of bunching firms, suggesting that 2.017 percent of the 210,306 firms considered within the fixed bandwidth manipulate their employment levels. Hence, there are 2,121 (=(0.02017*210,306)/2) employment manipulators in total.[30] As both types of firms, i.e., *noncompliers* and *perfect compliers*, may be *B-Firms* according to Section 3.2, I expect firms of each type to bunch below the threshold.

To assess how many of the 2,121 bunching firms are *B-perfect compliers*, I restrict my sample to firms that employ at least one disabled worker and estimate the bunching and threshold effects for this subsample of 121,382 observations. The result is an estimated bunching effect of -1.413 and an estimated threshold effect of 0.262 (see also Figure B.1 and Table B.3 in the Appendix). This result suggests that 858 of the 2,121 bunching firms are *B-perfect compliers* and 1,263 firms are *B-noncompliers*.[31]

To bound the threshold effect, I hypothetically reassign all potential bunching firms from a firm size of 39 employees to a firm size 40 while keeping the number of disabled workers constant (i.e., a total of 1,263 firms would still employ zero disabled workers, and 858 firms would still employ one disabled worker). I then recalculate the raw difference in the mean number of disabled workers among firms with 39 employees and among those with 40 employees. This yields a difference of 0.161. The original raw difference in the mean number of disabled workers in those firms was 0.348, so the bias amounts to 0.348-0.161=0.187. Using this bias calculation to bound the naive threshold effect of 0.388 suggests that the lower bound of the effect is 0.201. Thus, even after taking potential bunching into account, I still obtain to a positive threshold effect. Taken together, my estimates suggest that the employment quota indeed induces firms to employ more disabled workers, but dependent on the extent of bunching, the real threshold effect may be considerably smaller than the naive effect.

[30] The following example illustrates why this number is divided by two: Imagine 100 firms on either side of the threshold. Now assume that ten firms bunch and purposely stay below the threshold. Now, there are 110 firms below and 90 firms above the threshold. The resulting difference in the number of firms is 20 – twice the number of bunching firms (Lalive/Wuellrich/Zweimüller, 2013).

[31] As a robustness check, I restrict my sample to firms that employ at least two disabled workers. As these firms (*overcompliers*) do not face additional costs at the threshold when they are below the threshold, bunching should not occur. In fact, Figure B.2 in the Appendix suggests that *bunching below the threshold* is not relevant for *overcompliers*. According to the formal test by Cattaneo/Jannson/Ma (2020), firm size density *increases* significantly for *overcompliers* at the threshold of 40 employees. This is plausible, as it is in line with the institutional regulations under which firms above the threshold are obliged to employ two and more disabled workers. Thus, the share of these firms probably increases at the threshold.

5.5 Bunching Behavior

To shed additional light on the bunching behavior of firms, I use the characteristics of the firms' workforces, which may be affected by bunching, as unintended outcome variables. Specifically, I look examine firm and employee productivity, firm dynamics and workforce composition.

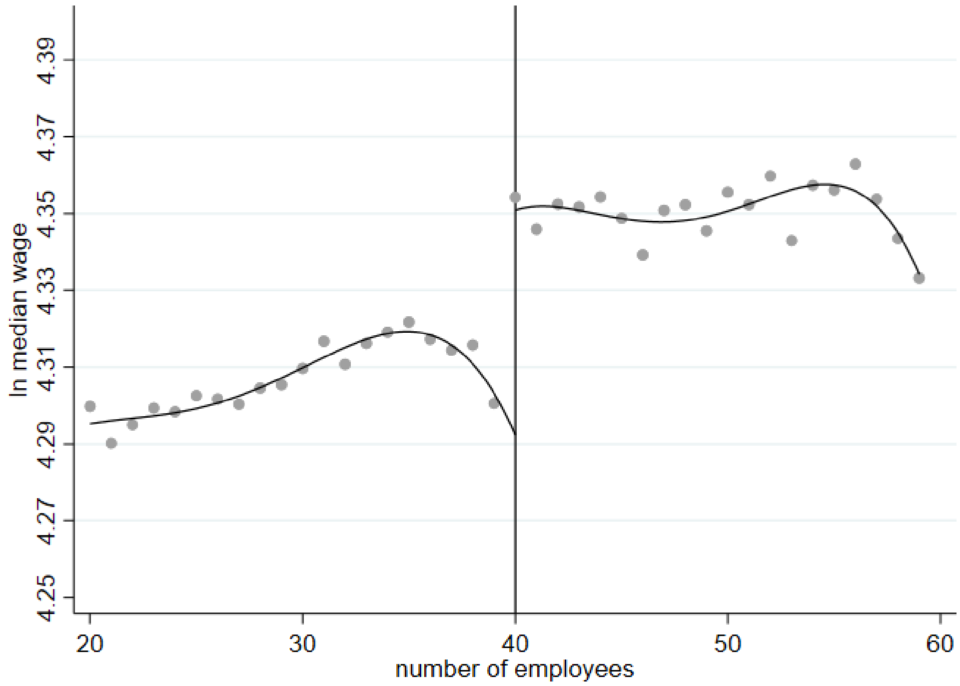
The graphical inspection of selected variables shown in Figures 7, 8 and 9 suggests that there are discontinuities at the threshold: Median wages are considerably lower in firms below the threshold. In addition to wages, I use firm and person fixed effects – also called AKM effects – as a proxy for the firm and employee productivity provided by Bellmann et al. (2020).[32] The illustration of the firm fixed effects analysis in Figure B.3 in the Appendix is very similar to that for wages. For person fixed effects, the graphical inspection also indicates a substantial discontinuity at the threshold (see Figure B.4 in the Appendix).[33] Furthermore, the share of regularly employed workers in firms below the threshold is lower than in firms above the threshold, whereas the share of marginally employed workers is higher. Last, firms just below the threshold have considerably lower employment growth. Table 4 reports the estimated discontinuities in the considered variables at the 40-employee threshold, again with different specifications (p=1 and p=4). The pattern of results supports the hypothesis that some firms bunch below the threshold and adjust their workforce when facing an increase in labor costs. Specifically, firms below the threshold substitute regularly employed workers with marginally employed workers who do not count toward the calculation of firm size (see Section 3.1). The significant discontinuities in wages and in AKM firm and person fixed effects suggest that adjusting the workforce may lead to lower productivity among bunching firms. These discontinuities may also result from selection, as low-productivity firms may be more incentivized to bunch since they face (relatively) higher costs at the threshold (see also the discussion and analysis of the heterogeneous effects between low- and high-wage firms in Section 5.7.1). In summary, the overall picture suggests that the increase in labor costs due to the noncompliance fine at the threshold of 40 employees is highly correlated with firm dynamics, firm productivity and firm employment structures.

When distinguishing between *nonompliers*, *perfect compliers* and *overcompliers*, the results in Table 4 show that the significant coefficients are mainly driven by *noncompliers*.[34] For *overcompliers*, in contrast, the coefficients are not significantly different from zero for any of

[32] Table A.3 in the Appendix explains the construction of the AKM effects in more detail.
[33] I use the person fixed effects for 2003-2010 provided by Bellmann et al. (2020) for individuals in the Integrated Employment Biographies (IEB) employed in firms sized 28-51 in 2010. Thus, I obtain a baseline sample of 1,479,831 individuals.
[34] The graphical illustrations for the different types of firms are shown in Figures B.5, B.8, B.9 and B.10 in the Appendix.

the alternative outcomes. Koller/Schnabel/Wagner (2006) analyzed employment growth for firms around the (former) threshold within the German disabled worker law in 1999 and 2000. In line with my results, those authors also found evidence of a significant and substantial decline in employment growth among firms below the second threshold that do not employ any disabled workers.[35] Taken together, the results suggest that bunching behavior is particularly pronounced among those firms just below the threshold that face the highest costs at the threshold, as discussed theoretically in Section 3.2.

Figure 7: Wages

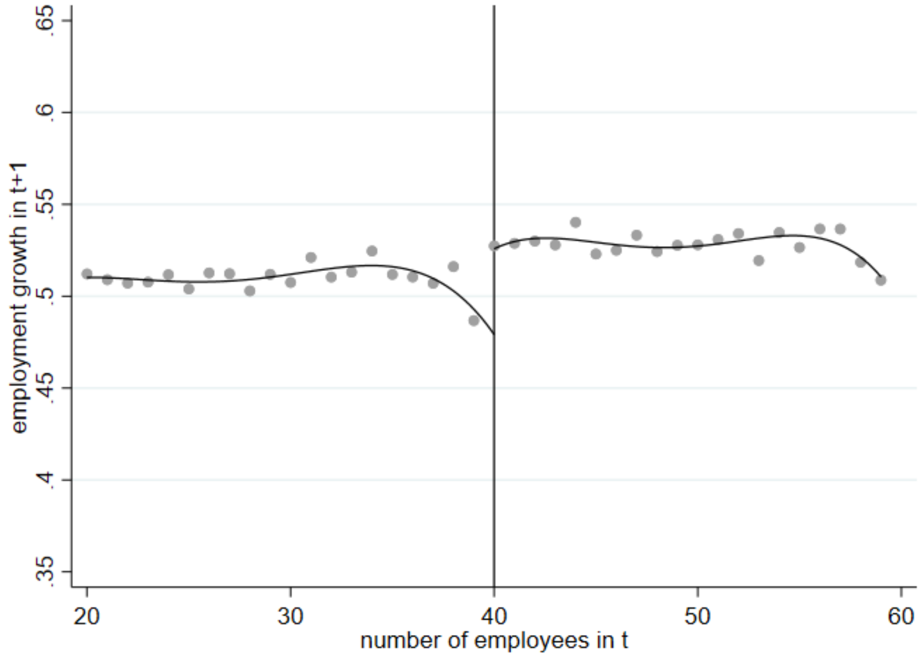


ln Median Wages

Note: This graph plots the ln of median wages by firm size around the threshold of 40 employees. The black line approximates the functional form of the running variable (here with polynomial order fit p=4 and bandwidth h_{below}=20 and h_{above}=19).
Source: BsbM and BHP 2004–2011, own calculations.

[35] Koller/Schnabel/Wagner (2006) estimate a different model specification. Specifically, the authors use a probit model, with the probability of growth in t+1 as the dependent variable. Their coefficient of interest is the interaction between being just below the former threshold (i.e., having 24 employees) and employing fewer than two disabled workers (i.e., not complying with the law). The coefficient on this interaction is -1.336 and is significant at the 5 percent level. Through simulations, the authors quantify the decline in growth as approximately 22.9 percentage points. The probable best approximation to this specification is to estimate the threshold effect on employment growth for all noncomplying firms (i.e., *noncompliers* and *perfect compliers*). This estimation (with p=4 and the MSE-optimal bandwidth calculation) results in a coefficient of 0.211, which is significantly different from zero at the one percent level. Thus, the effect is very similar to that found by Koller/Schnabel/Wagner (2006).

Figure 8: Firm Dynamics



Employment Growth in t+1

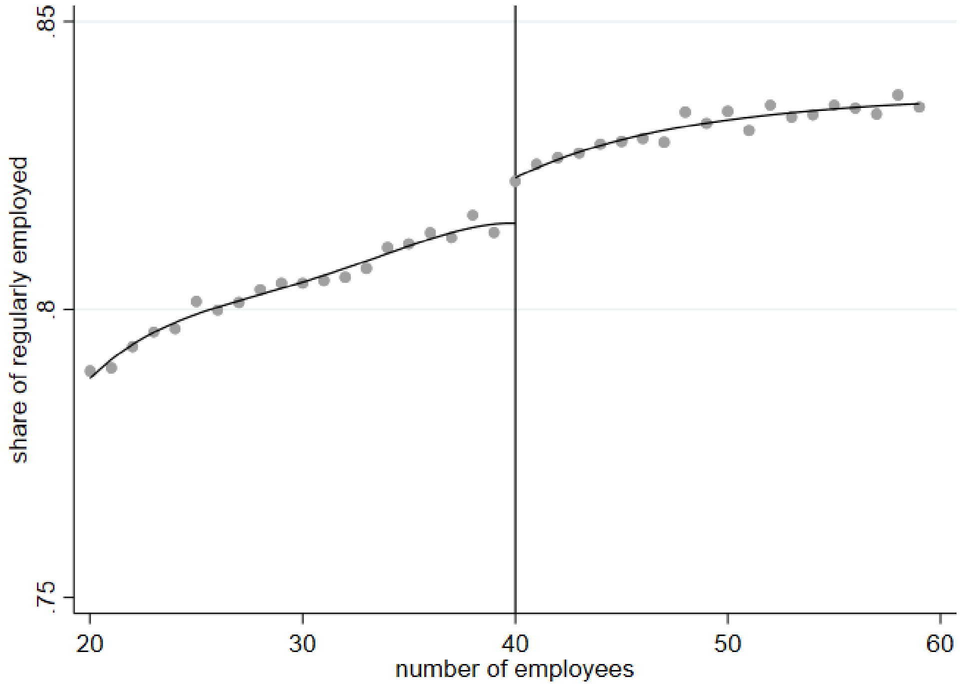
Note: This graph plots employment growth by firm size around the threshold of 40 employees. Employment growth is defined via a dummy variable that equals 1 if a firm has more employees (according to the BsbM) in t+1 than in t and 0 otherwise. The black line approximates the functional form of the running variable (here with polynomial order fit p=4 and bandwidth h_{below}=20 and h_{above}=19).
Source: BsbM and BHP 2004–2011, own calculations.

5.6 Robustness Checks: Placebos and Donuts

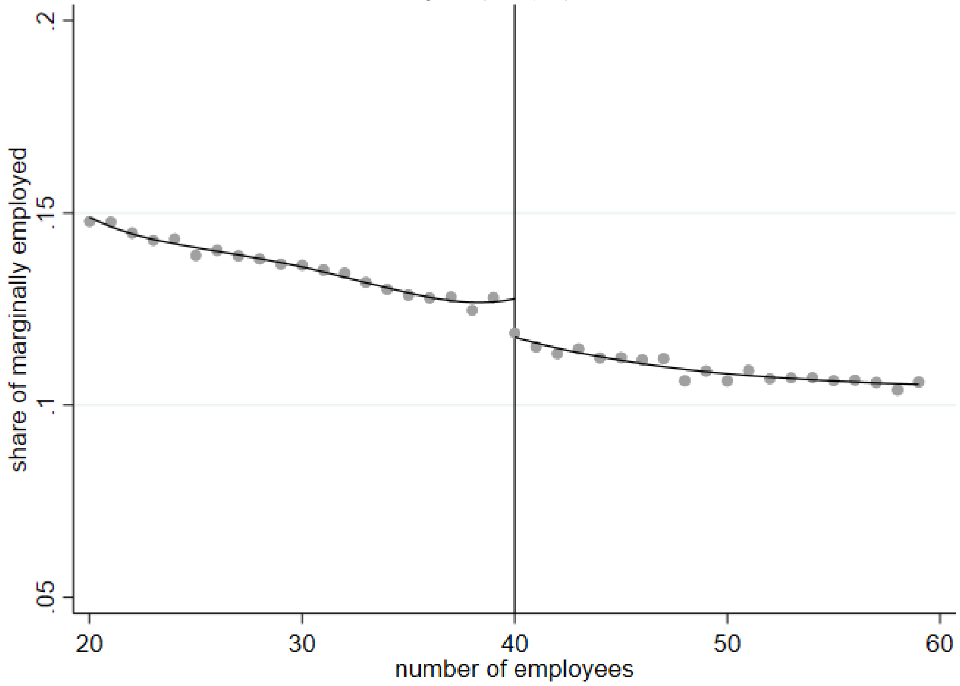
To assess the credibility of my results, I perform several robustness checks. My first test is the use of placebo thresholds. For this, I estimate the discontinuities in the number of disabled workers per firm at firm sizes where there should be no discontinuities. Figure 10 shows the estimated discontinuities for the specification with p=4 and an optimal bandwidth of firm sizes 28-51 (including the true threshold at a firm size of 40).[36] The pattern of estimates displays a clear-cut peak at the true threshold. For some placebo thresholds, e.g., firm sizes of 28, 41, 42, 45 or 46 employees, the 95 percent confidence interval does not include 0. This is in contrast to the graphical illustration in Figure 5, which suggests that there are no discontinuities at these firm sizes. Specifications with different

[36] Note that the German labor law has additional regulations with other thresholds, which may also be relevant for the employment of disabled workers. One example is the threshold of 30 employees with regard to insurance for continued payment (“Entgeltfortzahlungsversicherung”). In Germany, employees are entitled to sick pay that is paid by their employer during the first six weeks of an illness. Health insurance reimburses employers for some of these costs through the insurance for continued payment. This insurance is obligatory for employers who do not employ more than 30 employees. For an overview of the German regulations with thresholds, see Koller (2010).

Figure 9: Regular and Marginal Employment



(A) Share of Regularly Employed Workers



(B) Share of Marginally Employed Workers

Note: This graphs plot (A) the share of regularly employed workers and (B) the share of marginally employed workers by firm size around the threshold of 40 employees. The black line approximates the functional form of the running variable (here with polynomial order fit p=4 and bandwidth h_{below}=20 and h_{above}=19).
Source: BsbM and BHP 2004–2011, own calculations.

Table 4: Bunching Behavior

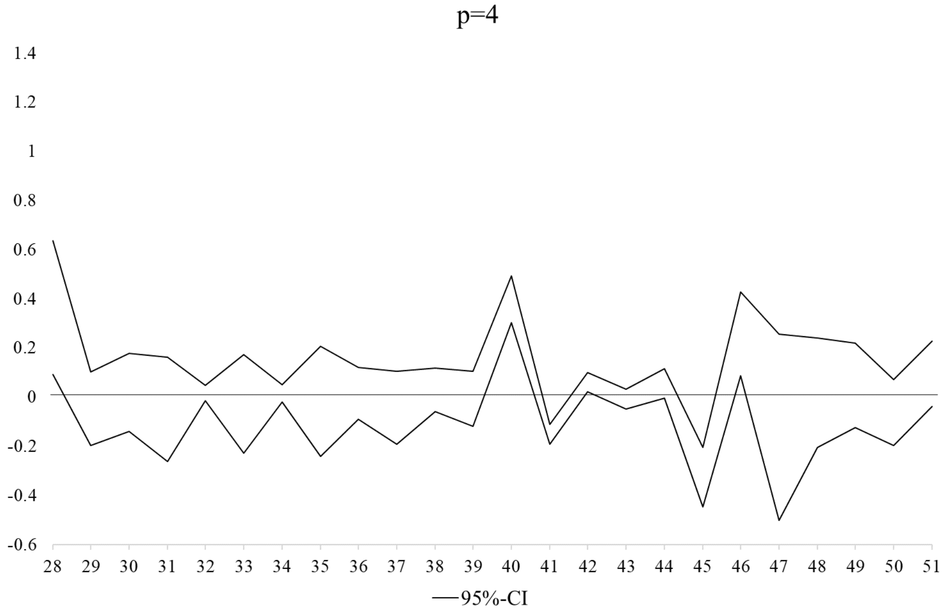
Dependent Variable	p = 1 Total	p = 4 Total	Noncompliers	Perfect Compliers	Over-compliers
	(1)	(2)	(3)	(4)	(5)
Sociodemographic Structure					
Share of Females	-0.003	-0.011	-0.006	-0.015	-0.012
Share of Germans	0.005***	0.012**	0.023**	0.004	-0.000
Employment Structure					
Median Wages (ln)	0.050***	0.088***	0.095***	0.048*	0.036
Firm Fixed (AKM) Effects	0.029***	0.050***	0.048***	0.036**	0.022
Person Fixed (AKM) Effects	0.039***	0.033***	0.049***	0.029	-0.005
Share of Regularly Employed Workers	0.014***	0.016***	0.019***	0.015	0.007
Share of Marginally Employed Workers	-0.015***	-0.024***	-0.037***	-0.015	-0.004
Share of Apprentices	0.000	0.002	0.009	-0.003	-0.000
Share of Full-Time Workers	0.008**	0.015	0.012	0.022*	0.020
Share of Part-Time Workers	0.003	0.008	0.014	-0.005	-0.005
Skill Structure					
Share of Low-Skilled Workers	-0.005***	-0.010	-0.016*	-0.009	0.002
Share of Medium-Skilled Workers	-0.003	0.006	0.017	0.004	-0.021
Share of High-Skilled Workers	0.009***	0.007	0.004	0.002	0.017
Firm Dynamics					
Employment Growth in t+1	0.071***	0.229***	0.353***	0.116*	0.033

Notes: This table shows the estimation results for the effect of the threshold of 40 employees on alternative outcome variables. *Noncompliers*, *perfect compliers* and *overcompliers* are firms below the threshold that employ zero, exactly one or at least two disabled worker(s), respectively. All estimations are estimated by using the MSE-optimal bandwidth for either side of the threshold. Standard errors are clustered at the firm level. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels.
Source: BsbM and BHP 2004–2011 (2004–2010 for firm fixed effects, 2010 for person fixed effects), own calculations.

polynomial orders show that although there are significant discontinuities at some placebo thresholds, the robustness of these estimations seems to be low: While the estimated discontinuity at the true threshold is positive and highly significant in all specifications, the significance of the coefficients for the placebo thresholds varies considerably depending on the specification. Furthermore, in terms of magnitude, the coefficient at the true threshold is substantially larger than the coefficients at the placebo thresholds in most cases (see Figures B.11, B.12 and B.13 in the Appendix). Taken together, the overall pattern confirms the credibility of the estimated discontinuity at the true threshold of 40.

Next, Figure 5 suggests that, in particular, firms with 39 and 40 employees violate the otherwise quite linear relationship between firm size and the mean number of disabled workers. Thus, as a further robustness check, I perform donut estimations and exclude those firms (and other combinations of firms near the threshold) and calculate the

Figure 10: Placebo Thresholds



Note: The graph shows the effects of the placebo thresholds on the mean number of disabled workers with p=4 and an MSE-optimal bandwidth on either side of the threshold (controlling for predetermined covariates). All thresholds except for the 40-employee threshold are placebo thresholds. The 95% confidence interval refers to the robust CI estimated with the *rdrobust* command in Stata. As the point estimates could be outside the robust CIs, only the interval boundaries are shown. Standard errors are clustered at the firm level.
Source: BsbM and BHP 2004–2011, own calculations.

bunching and threshold effects again for this subsample. Table 5 shows the results. Note that I now use a linear specification, as the overall relationship between firm size and the number of disabled workers – when excluding the nonlinear developments near the threshold – appears to be linear. Let us first turn to the threshold effects. Compared to the coefficients from the baseline specifications, the coefficients from the donut estimations are smaller but still highly significant. This confirms the notion that part of the estimated naive threshold effect is biased by firms bunching below the threshold. Regarding bunching, the estimations show that the bunching effects are considerably smaller than in my baseline estimations, indicating that firm size manipulations occur mainly among firms located directly around the threshold.

Overall, the significant threshold effects estimated for the subsamples without firms near the threshold confirm my main results: Even though bunching is present, the regulation seems to positively affect the number of disabled workers in firms.

Table 5: Donut Estimations

	Baseline Estimation	Donut Estimations: Excluding Firms of Firm Size		
		39	39+40	38+39
	(1)	(2)	(3)	(4)
		Bunching Effects		
Coefficient	-2.017	-0.608**	-0.521*	-0.568
Robust CI	[-5.521; 1.702]	[-1.459; -0.080]	[-1.364; 0.052]	[-2.396; 0.992]
# of Observations	16	15	14	14
		Threshold Effects		
Coefficient	0.388***	0.203***	0.164***	0.172***
Robust CI	[0.185; 0.668]	[0.233; 0.349]	[0.174; 0.301]	[0.155; 0.366]
Polynomial Order p	4	1	1	1
Covariates Included	yes	yes	yes	yes
# of Observations	210,306	192,965	182,616	177,260

Notes: This table shows the estimation results for the effect of the threshold on the number of disabled workers in a firm (threshold = firm size of 40 employees). The bandwidth for all estimations is h_{below}=8 and h_{above}=9. Basic covariates include firm age, regional characteristics (federal state) and industry. Standard errors are clustered at the firm level. *, **, *** denote statistical significance at the 10%, 5% and 1% levels.
Source: BsbM and BHP 2004–2011, own calculations.

5.6.1 Further Robustness Tests

Next, I exclude public administration firms, as the share of firms in this sector differs below and above the threshold (see Section 4.3). The estimated coefficients are similar to those from the baseline estimation (see Table B.6 in the Appendix). Thus, I can conclude that public administration firms do not alter my basic results. Furthermore, I exclude firms that are identifiable as multiestablishment firms.[37] The results for the threshold and bunching effects and – more importantly – the results regarding bunching behavior are also robust to this exclusion (see Table B.7 and Table B.8 in the Appendix). Last, altering the specification, for example, by using different kernel weights or using a different bandwidth selector, does not alter my results, either.[38]

[37] I can identify a firm as multiestablishment firms in the BsbM data as soon as it reports a disabled worker who is not working in the main establishment. In this manner, I exclude 1,782 firm-year observations (of firms with 20 to 59 employees). Note, however, that this exclusion is selective in the sense that I exclude only firms employing at least one disabled worker.
[38] Results not shown but available upon request.

5.7 Heterogeneous Effects

Based on the theoretical considerations described in Section 3, I now turn to a discussion of the potential heterogeneity in the bunching and treatment effects. Specifically, I differentiate between low- and high-wage firms and analyze different industries.

5.7.1 Low-Wage and High-Wage Firms

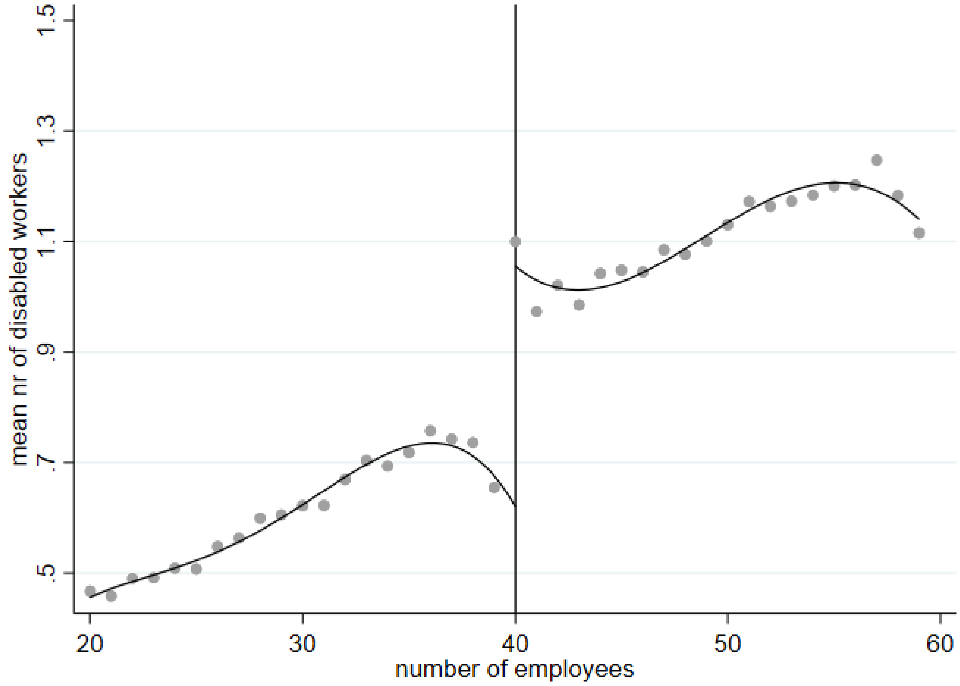
First, with regard to low- and high-wage firms, the share of the noncompliance fine τ relative to wages is substantially higher for low-wage firms than for high-wage firms: Among firms with 20-59 employees, the relative shares of the noncompliance fine are approximately 7.1 percent (τ_1) and 12.2 percent (τ_2) of wages among firms in the first quartile of the wage distribution (low-wage firms).[39] In contrast, these shares are only approximately 3.0 percent (τ_1) and 5.1 percent (τ_2) of wages among firms in the fourth quartile (high-wage firms). Thus, the (relative) importance of the noncompliance fine differs considerably between these groups of firms. For a given wage w and disabled worker productivity p, a relatively larger noncompliance fine τ leads to an increase in the number *B-firms* among firms for which $p < w$ and thus a larger bunching effect among low-wage firms. Likewise, a relatively larger fine leads to an increase in the number of *G-firms* among firms for which $p > w$. As a consequence, I also expect a larger threshold effect among low-wage firms (see Section 3.1). For the empirical analysis, I group the firms based on quartiles of the wage distribution. The graphical analysis shown in Figure 11 suggests that the threshold effect among firms in the first quartile of the wage distribution is larger than that among firms in the fourth quartile of the wage distribution. The estimated threshold and bunching effects shown in Table 7 confirm this notion: The threshold effect is substantially larger among low-wage firms. The naive threshold effect among low-wage firms is 0.588, compared to 0.235 among high-wage firms, and the lower bound of this effect is 0.301 among low-wage firms, compared to 0.072 among high-wage firms. Furthermore, bunching is present among both types of firms but is also more pronounced among low-wage firms. In summary, these results support the hypothesis that the threshold and bunching effects are larger among low-wage firms.

5.7.2 Effects by Industry

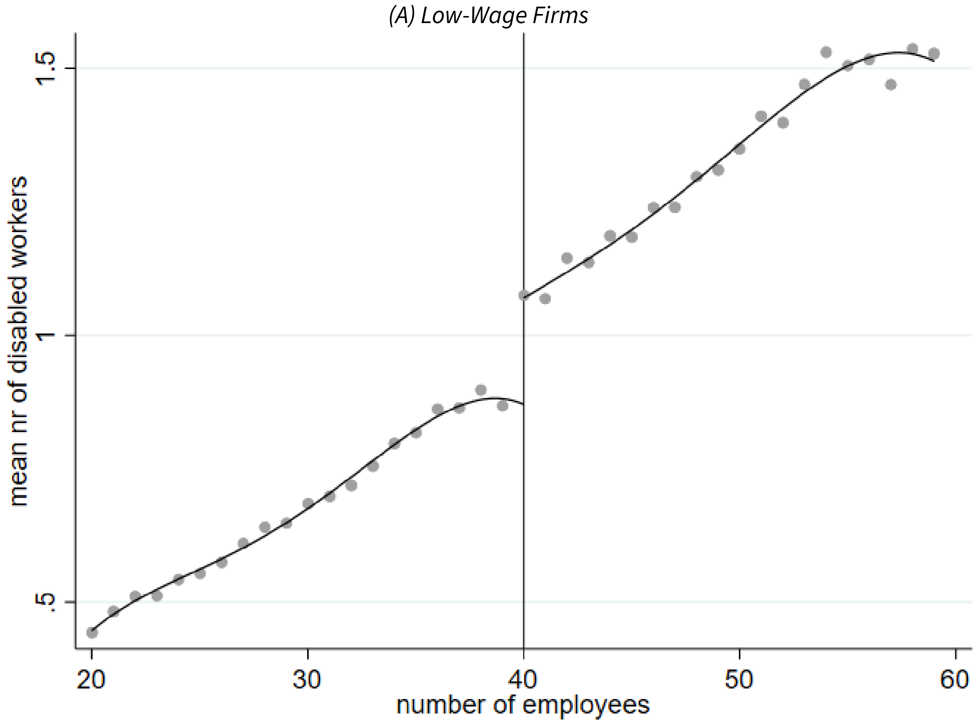
I next estimate the bunching and threshold effects stratified by industry. The results displayed in Table B.7 show that the largest (naive) threshold effects are found in the industries agriculture/fishery, construction and traffic/communication industries. Bunching

[39] The wage distribution is based on the median value of gross daily wages for full-time employees.

Figure 11: Mean Number of Disabled Workers



(A) Low-Wage Firms



(B) High-Wage Firms

Note: These graphs plot the mean number of disabled workers in (A) low-wage firms and (B) high-wage firms by firm size around the threshold of 40 employees. The black line approximates the functional form of the running variable (here with polynomial order fit p=4 and bandwidth h_{below}=20 and h_{above}=19).
Source: BsbM and BHP 2004–2011, own calculations.

Table 6: Heterogeneous Effects by Firm Wages

	Observations	Threshold Effect (TE)		Bunching Effect	Lower Bound
		p = 1	p = 4	p = 4	of TE
	(1)	(2)	(3)	(4)	(5)
		Firms in 1st Quartile of Wage Distribution			
MSE-Optimal Bandwidth		0.473***	0.588***	-2.963**	
Fixed Bandwidth	61,462	0.307***	0.590***	-2.598*	0.310
		Firms in 2nd Quartile of Wage Distribution			
MSE-Optimal Bandwidth		0.369***	0.398***	-1.913**	
Fixed Bandwidth	57,386	0.273***	0.392	-2.126	0.199
		Firms in 3rd Quartile of Wage Distribution			
MSE-Optimal Bandwidth		0.307***	0.334***	-1.643**	
Fixed Bandwidth	59,242	0.236***	0.318	-1.519*	0.151
		Firms in 4th Quartile of Wage Distribution			
MSE-Optimal Bandwidth		0.178***	0.233***	-0.826	
Fixed Bandwidth	74,540	0.126***	0.235***	-1.099**	0.072

Notes: This table shows the estimation results for the threshold effects (dependent variable: mean number of disabled workers in a firm) around the 40-employee threshold and the bunching effects (dependent variable: firm size density in %) stratified by firms' median daily wage (quartiles). Basic covariates include firm age and regional characteristics (federal state). Standard errors are clustered at the firm level. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels. The fixed bandwidth is the MSE-optimal bandwidth from the estimation with polynomial order p=4, rounded up to the nearest whole number.
Source: BsbM and BHP 2004–2011, own calculations.

is particularly pronounced in construction, traffic/communication and the public sector. When bounding the threshold effects by following the bounding exercise in 5.4, the largest lower bounds emerge in the agriculture/fishery, construction and other services sectors. Industries may serve as a proxy for different workplace characteristics. First, assuming that wages are equal between disabled and nondisabled workers, as done in Section 3.1, is accurate mainly for firms in industries with high levels of collective bargaining coverage. However, the results displayed in Table B.7 do not indicate a clear pattern in terms of the level of collective bargaining coverage: On the one hand, there are no significant threshold effects among firms in energy/mining and banking/insurance – both sectors typically characterized by a relatively high level of collective bargaining coverage (Ellguth/Kohaut, 2004, 2012).[40] On the other hand, there are substantial threshold (and bunching) effects among firms both in industries with high collective bargaining coverage (such as construction and public administration) and in industries with low collective bargaining coverage (such as other services and traffic/communication). Second, industries may have different working conditions, in particular different shares of physically demanding tasks. As physical disabilities still account for the majority of disabilities (Statistisches Bundesamt,

[40] Note that collective bargaining coverage also depends on establishment size. According to Ellguth/Kohaut (2012), 53 (39) percent of West German establishments with 10 to 49 (50 to 199) employees were not covered by a collective bargaining agreement in 2011.

2011), the share of physically demanding tasks in an industry may serve as a proxy for the average productivity gap between disabled and nondisabled workers. Sectors in which the average productivity of a disabled worker differs substantially from that of a nondisabled worker (i.e., $p \ll P$) probably have a higher share of firms in which $p < w$ (and thus a higher share of bunching (*B*-)firms). The large bunching effect in the construction sector (-2.562) is in line with these considerations, as this industry is characterized by a high share of physically demanding tasks (Kroll, 2011).

Table 7: Heterogeneous Effects by Industry

	Observations	Threshold Effect (TE)		Bunching Effect	Lower Bound
		p=1	p=4	p=4	of TE
	(1)	(2)	(3)	(4)	(5)
			Agriculture/Fishery		
MSE-Optimal Bandwidth		0.226*	0.591**	-1.194***	
Fixed Bandwidth	4,356	0.218*	0.647	-1.519	0.420
			Energy/Mining		
MSE-Optimal Bandwidth		0.235	0.279	-1.554	
Fixed Bandwidth	2,392	0.209	0.298	-1.591	-
			Manufacturing		
MSE-Optimal Bandwidth		0.331***	0.337**	-1.704**	
Fixed Bandwidth	63,118	0.228***	0.336	-1.654	0.137
			Construction		
MSE-Optimal Bandwidth		0.255***	0.536**	-2.517*	
Fixed Bandwidth	18,336	0.229***	0.536	-2.562	0.413
			Wholesale		
MSE-Optimal Bandwidth		0.301***	0.372***	-1.821**	
Fixed Bandwidth	46,454	0.198***	0.372*	-1.724*	0.205
			Traffic/Communication		
MSE-Optimal Bandwidth		0.352***	0.506***	-2.785*	
Fixed Bandwidth	16,763	0.257***	0.513*	-2.476*	0.241
			Banking/Insurance		
MSE-Optimal Bandwidth		0.101	0.081	0.187	
Fixed Bandwidth	3,151	0.039	-0.009	1.072	-
			Other Services		
MSE-Optimal Bandwidth		0.324***	0.428***	-2.053**	
Fixed Bandwidth	36,172	0.278***	0.569*	-2.046	0.362
			Public Administration (PA)		
MSE-Optimal Bandwidth		0.334***	0.396***	-1.191	
Fixed Bandwidth	37,661	0.271***	0.377	-1.258**	0.186
			Public Sector (w/o PA)		
MSE-Optimal Bandwidth		0.355***	0.371*	-2.903*	
Fixed Bandwidth	11,666	0.265***	0.349	-1.818*	0.110

Notes: This table shows the estimation results for the threshold effects (dependent variable: mean number of disabled workers in a firm) around the 40-employee threshold and the bunching effects (dependent variable: firm size density in %) stratified by industry. Basic covariates include firm age and regional characteristics (federal state). Standard errors are clustered at the firm level. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels. The fixed bandwidth is the MSE-optimal bandwidth from the estimation with polynomial order p=4, rounded up to the nearest whole number. For “energy/mining” and “banking/insurance” industries, no significant threshold effects were identified and thus no lower bounds were calculated.
Source: BsbM and BHP 2004–2011, own calculations.

5.8 Results for the 60-Employee Threshold

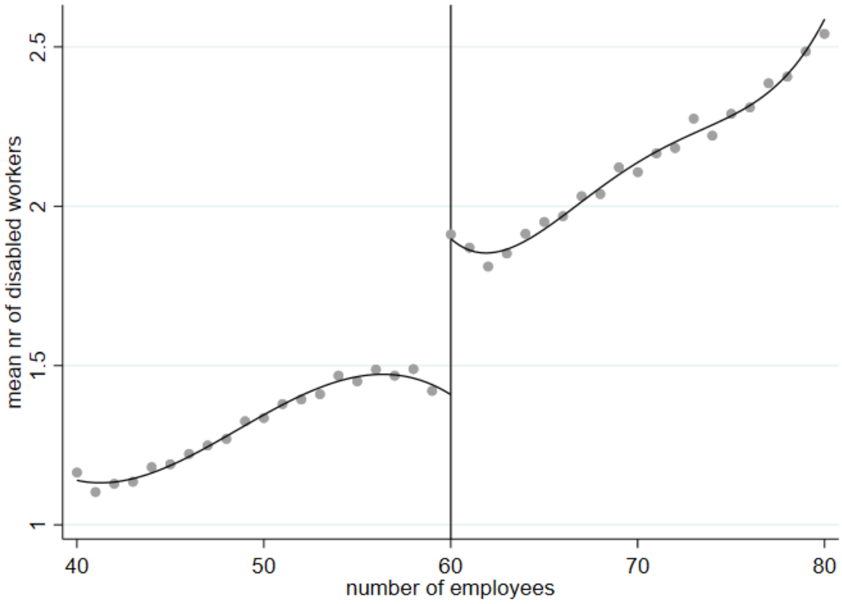
In this section, I check whether a similar pattern is visible at the third threshold of 60 employees. Firms with 40 to less than 60 employees must employ at least two disabled workers, while firms with 60 or more employees are obliged to employ at least three (=five percent) disabled workers. Note, however, that there are other threshold rules for the 60-employee threshold in the German labor law.[41] Thus, the following analyses are primarily exploratory and serve as a robustness check for the results for the 40-employee threshold.

I restrict my sample to firms around the threshold of 60 employees. Regarding the intended effect, the graphical illustration again indicates a considerable discontinuity in the mean number of disabled workers between firms below and above this threshold (see Figure 12). The histogram for the firm size distribution suggests that bunching is also present at this threshold (see Figure B.14 and, for the results of the formal test, Table B.4 in the Appendix). Furthermore, the plots of and estimations for selected alternative outcome variables regarding the employment and wage structures as well as firm dynamics are similar to the patterns in those outcome variables near the 40-employee threshold (see Figures B.15, B.16, B.17 and Table B.5 in the Appendix). Table 8 gives an overview of the formally estimated bunching and threshold effects for the 60-employee threshold. All threshold effects estimated with MSE-optimal bandwidths are significantly different from zero at least at the 10 percent level. In terms of size, the threshold effects for the 60-employee threshold are larger than those for the 40-employee threshold, while the sizes of the bunching effects are similar. This result is consistent with the results of Lalive/Wuellrich/Zweimüller (2013), who also find larger effects at higher thresholds (albeit without evidence of bunching at higher thresholds). Repeating the bounding exercise described in Section 5.4 yields a lower bound of the threshold effect of 0.380.[42] In sum, the analyses for the 60-employee threshold largely confirm the results obtained for the 40-employee threshold.

[41] For example, according to the Protection Against Dismissal Act (*Kündigungsschutzgesetz*), an employer with 60 or more employees must report a layoff of 10 percent of the workforce or of more than 25 employees to the employment agency.

[42] Note that there are four firm types around the threshold of 60 employees: *noncompliers* with employment of disabled workers $D = 0$, *undercompliers* with $D = 1$, *perfect compliers* with $D = 2$ and *overcompliers* with $D \geq 3$. I estimate the share of *B-undercompliers* and *B-perfect compliers* among all bunching firms by restricting the sample to firms with at least one or at least two disabled workers, respectively. As a result, I find 237 *B-perfect compliers*, 765 *B-undercompliers* and 278 *B-noncompliers* among the 1,281 total bunching firms.

Figure 12: Number of Disabled Workers



Note: This graph plots the average number of disabled workers by firm size around the threshold of 60 employees. The black line approximates the functional form of the running variable (here with polynomial order fit p=4).
Source: BsbM and BHP 2004–2011, own calculations.

Table 8: Threshold and Bunching Effects for the 60-Employee Threshold

	60-Employee Threshold – Bunching Effects				
	(1)	(2)	(3)	(4)	(5)
Coefficient		-1.691**	-1.905*	-2.006*	-2.161
Robust CI		[-3.482; -0.213]	[-4.202; 0.076]	[-4.528; 0.238]	[-7.084; 3.381]
Bandwidth h		6.75; 8.79	8.67; 12.53	11.51; 15.53	8; 14
Polynomial Order p		2	3	4	4
# of Observations		15	21	27	21
	60-Employee Threshold – Threshold Effects				
	(1)	(2)	(3)	(4)	(5)
Coefficient	0.462***	0.498***	0.529***	0.653***	0.653**
Robust CI	[0.410; 0.574]	[0.417; 0.618]	[0.420; 0.671]	[0.451; 0.902]	[0.160; 1.178]
Bandwidth h	3.48; 3.58	5.61; 6.77	7.44; 9.74	7.84; 13.63	8; 14
Polynomial Order p	1	2	3	4	4
Covariates Included	yes	yes	yes	yes	yes
# of Observations	43,523	73,050	101,907	118,537	118,537

Notes: This table shows the estimation results for the bunching effects (dependent variable: firm size density in %) and the threshold effects (dependent variable: mean number of disabled workers in a firm around the 60-employee threshold). Basic covariates include firm age, regional characteristics (federal state) and industry. Standard errors are clustered at the firm level. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels. It is not possible to estimate the bunching effect in a linear specification (p=1) with the MSEoptimal bandwidth calculation due to the very small number of observations.
Source: BsbM and BHP 2004–2011, own calculations.

6 Summary and Conclusions

In Germany, firms with 40 or more employees are obliged to employ one additional worker with a disability. This paper analyzes the intended and unintended effects of this German employment quota for workers with disabilities. The intended effect refers to the effect of this regulatory threshold on firm demand for workers with disabilities, whereas the unintended effect refers to potential bunching below the threshold. Thus, my paper extends the literature on the effects of an increase in labor costs resulting from a disabled worker quota system.

I use this sharp increase in labor costs and adopt a threshold design, which is closely related to an RDD, to estimate these effects. However, the threshold design accounts for the fact that the running variable – firm size, in my case – is endogenous. My results indicate that the employment quota promotes the employment of disabled workers in firms located around the threshold. A naive estimate of the *intended*, or threshold, effect (when ignoring the bunching) suggests that threshold firms employ on average 0.388 more disabled workers. When analyzing the *unintended*, or bunching, effect, the results show that firms do indeed manipulate their employment due to the increase in labor costs at the threshold. The existence of bunching violates the assumptions necessary for identifying the unbiased effect of the regulatory threshold. However, based on the estimates about the extent to which firms manipulate, I am able to provide a lower bound for the threshold effect. After taking this bunching effect into account, I obtain a lower bound of 0.201, which is still positive, though considerably smaller. Thus, the German noncompliance fine does indeed increase compliance with the quota and promote the employment of disabled workers.

However, the quota also has unintended consequences that can be harmful to overall employment: Firms just below the threshold have a lower probability of increasing employment and a higher probability of substituting away from regularly employed workers. This is interesting, as previous research has found little evidence of firms bunching below the labor law thresholds in Germany. In view of the multitude of threshold regulations in German labor law, my findings shed new light on the relevance of such thresholds. Further research should therefore emphasize the evaluation of regulatory thresholds and firm adaptation to such regulations in other contexts.

Appendix

Appendix A: Definitions and Institutional Details

Table A.1: Calculation of Firm Size According to the Disabled Worker Law (§ 156 and § 157 SGB IX)

Excluded groups of workers	Apprentices (including special trainee positions for lawyers and teachers) Individuals who work less than 18 hours per week Individuals with a temporary contract of fewer than eight weeks Individuals whose employment is not primarily for pay (e. g., individuals whose employment is primarily for rehabilitation) Individuals participating in job creation schemes according to SGB III Individuals who are elected to their job after continuous practice
Temporal dimension	The relevant measure for the firm size is the *annual average* of the monthly number of positions.
Calculation details	Fractions of 0.5 or more are rounded down to the nearest whole number for firms with 20 to 59 positions Fractions of 0.5 or more are rounded up to the nearest whole number for firms with 60 or more positions

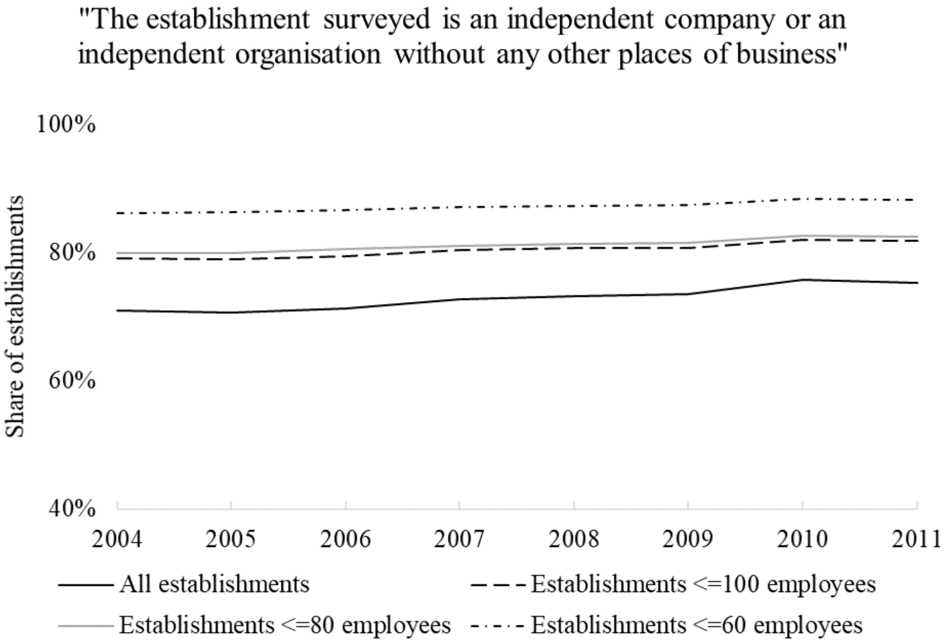
Source: § 156 and § 157 SGB IX, own illustration.

Table A.2: Additional Definitions Related to Firms/Establishments

Definitions of Firms and Establishments
Legal Definition of "Employer" (Firm) According to the Disabled Worker Law: Employers can be either a natural or a legal person under public or private law as well as a company of any kind. Consequently, all employees of the same employer are included, regardless of the number of establishments or other locations over which they are distributed.
Definition of "Establishment" in the Administrative Data: An establishment is a regionally and economically delimited unit in which employees work. An establishment may consist of one or more branch offices or workplaces belonging to one company (Schmucker et al., 2018).

Source: Schmucker et al., 2018, own illustration.

Figure A.1: Share of Individual Establishments



Notes: This graph shows the share of establishments that are independent companies or independent organizations without any other places of business. The survey is representative of all establishments in Germany (Ellguth/Kohaut/Möller, 2014).
Source: IAB Establishment Panel, 2004-2011, own calculations.

Table A.3: Person and Establishment Fixed Effects ("AKM Effects")

AKM-Effects
AKM person and establishment fixed effects stem from a wage decomposition pioneered by Abowd/Kramarz/Margolis (1999), implemented for Germany by Card/Heining/Kline (2013), and updated by Bellmann et al. (2020). These effects are derived from the following wage model: $$log(wage_{it}) = \alpha_i + \Psi_{J(i,t)} + x'_{it}\beta + \epsilon_{it},$$ where the log daily wages for worker i are the sum of a time-invariant person effect α_i, a time-invariant establishment effect $\Psi_{J(i,t)}$ for the establishment at which worker i is employed at time t, plus time-varying worker characteristics $x'_{it}\beta$, which affect all workers' wages equally at all establishments, and an error component ϵ_{it}, which is assumed to be independent of the right-hand-side variables. The estimates for the person effect α_i capture time-invariant individual characteristics that are rewarded equally across employers. Likewise, the index $x'_{it}\beta$ is interpreted as measuring the time varying worker characteristics that affect the productivity of worker i in all jobs. In x_{it}, an unrestricted set of year dummies and of quadratic and cubic terms in age fully interacted with education is included. Last, the establishment effect $\Psi_{J(i,t)}$ is interpreted as a proxy for an establishment productivity, as this effect represents the proportional pay premium (or discount) that is paid by establishment j to all employees (i.e., all those with $J(i,t) = j$) (Bellmann et al., 2020: p. 7).

Source: Abowd/Kramarz/Margolis (1999), Card/Heining/Kline (2013) and Bellmann et al. 2020.

Appendix B: Further Analyses

Table B.1: Manipulation Test by Cattaneo/Jannson/Ma (2020)

Cattaneo et al. Manipulation Test
(see Cattaneo/Jansson/Xinwei, 2018; Cattaneo/Jannson/Ma, 2020)

This test is based on a local polynomial density estimator and uses robust bias correction coupled with variance adjustments. Specifically, the manipulation test statistics in *rddensity* (Cattaneo/Jansson/Xinwei, 2018) take the form

$$T_p(h) = \frac{\hat{f}_{+,p}(h) - \hat{f}_{-,p}(h)}{\hat{V}_p(h)} \qquad T_p(h) \sim \mathcal{N}(0,1),$$

where h is the bandwidth and p, the polynomial order. $\hat{f}_{+,p}(h)$ and $\hat{f}_{-,p}$ are the local polynomial density estimators, and $\hat{V}_p(h)$ represents the corresponding SE estimator.
In Table B.2 and Table B.4, I estimate a model with data-driven MSE-optimal bandwidth choices (h_{MSE}), $p = 2$ and a triangular kernel weight. With $q \geq p + 1$, the manipulation test takes the form of an α-level test, with the null rejected if

$$T_q^2(h_{MSE,p}) > X_1^2(1 - \alpha)$$

$T_q^2(h_{MSE,p})$ gives an asymptotically valid distributional approximation of $q \geq p + 1$. Thus, the possible first-order bias in the statistic T_p^2 is removed by using a higher-order polynomial in the estimation of the densities and adjusting the SE formulas accordingly.

Source: Cattaneo/Jansson/Xinwei (2018) and Cattaneo/Jannson/Ma (2020).

Table B.2: Cattaneo et al. Estimator Test Statistics

	T		P > |T|
Robust	-21.2550		0.000
# of Observations		625,664	

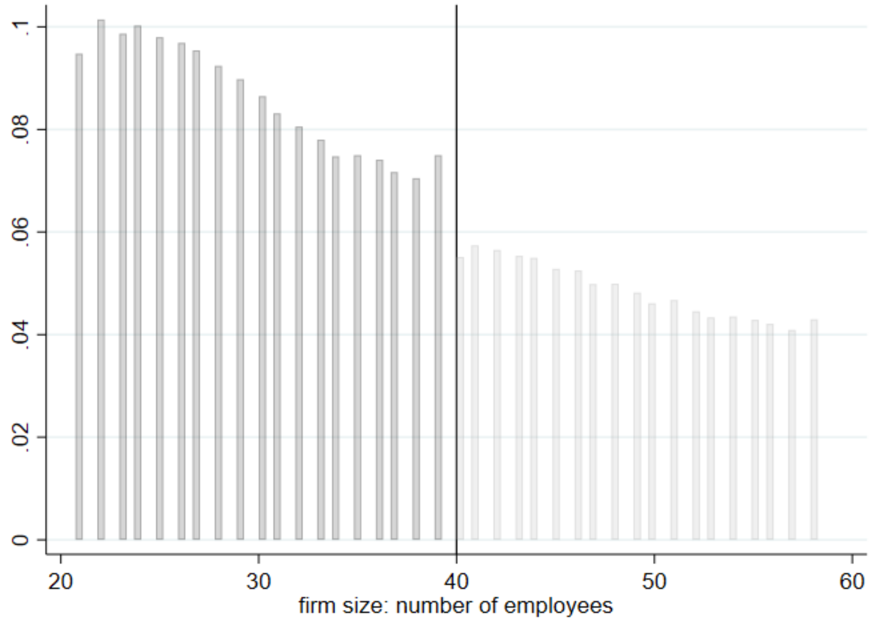
Source: BsbM and BHP 2004–2011, own calculations.

Table B.3: Effects among Firms with at Least One Disabled Worker

	Bunching Effect	Threshold Effect
Coefficient	-1.413	0.262**
Robust CI	[-3.818; 1.240]	[0.084; 0.645]
# of Observations	16	121,382

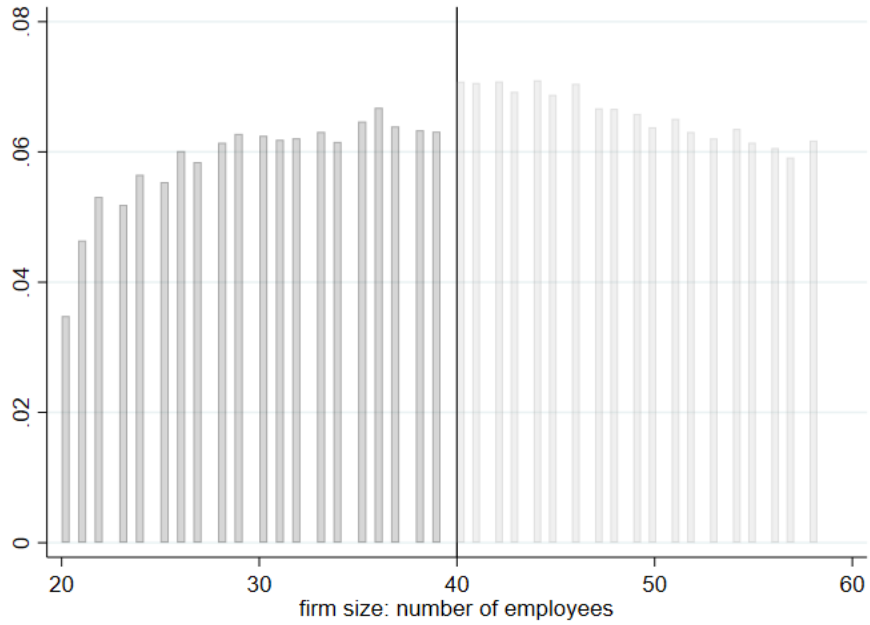
Notes: This table shows the estimation results for the threshold effects on the number of disabled workers in a firm only for firms which employ at least 1 disabled worker (h_{below}=8, h_{above}=9; p=4). Standard errors are clustered at the firm level. ** denotes statistical significance at the 5% level.
Source: BsbM and BHP 2004–2011, own calculations.

Figure B.1: Firm Size Density for Firms with at Least One Disabled Worker



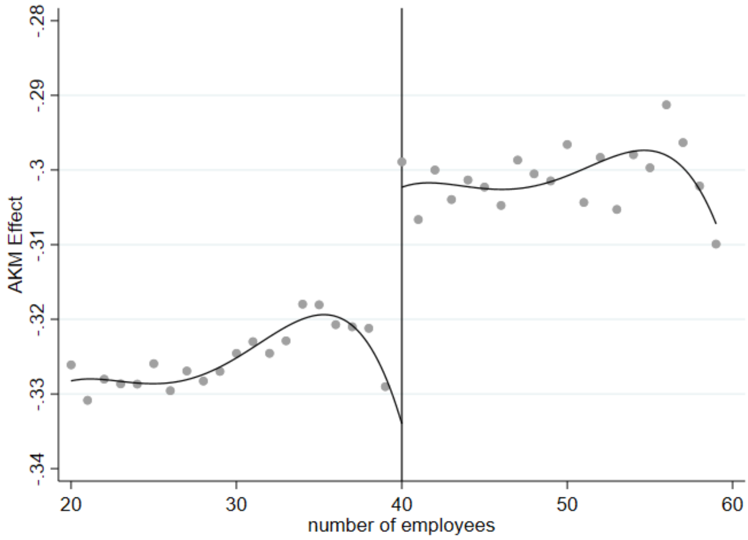
Notes: Histogram of firm size density for firms with at least one disabled worker around the threshold of 40 employees.
Source: BsbM and BHP 2004–2011, own calculations.

Figure B.2: Firm Size Density for Firms with at Least Two Disabled Workers



Notes: Histogram of firm size density for firms with at least two disabled workers around the threshold of 40 employees.
Source: BsbM and BHP 2004–2011, own calculations.

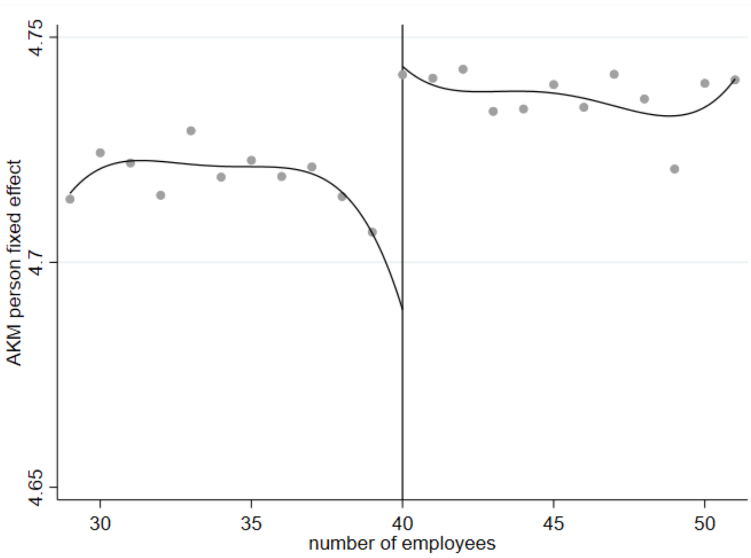
Figure B.3: Firm Productivity



AKM Firm Fixed Effects

Note: The graph plots the AKM firm fixed effects (see Table A.3) by firm size around the threshold of 40 employees. The black line approximates the functional form of the running variable (here with polynomial order fit p=4 and bandwidth h_{below}=20 and h_{above}=19).
Source: BsbM and BHP 2004-2010, own calculations.

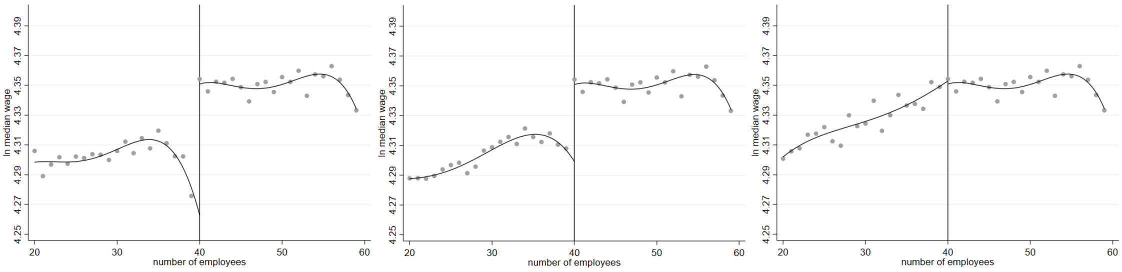
Figure B.4: Employee Productivity



AKM Person Fixed Effects

Note: This graph plots the AKM person fixed effects (see Table A.3) by firm size around the threshold of 40 employees. The black line approximates the functional form of the running variable (here with polynomial order fit p=4 and bandwidth h_{below}=12 and h_{above}=12).
Source: BsbM and Integrated Employment Biographies 2010, own calculations.

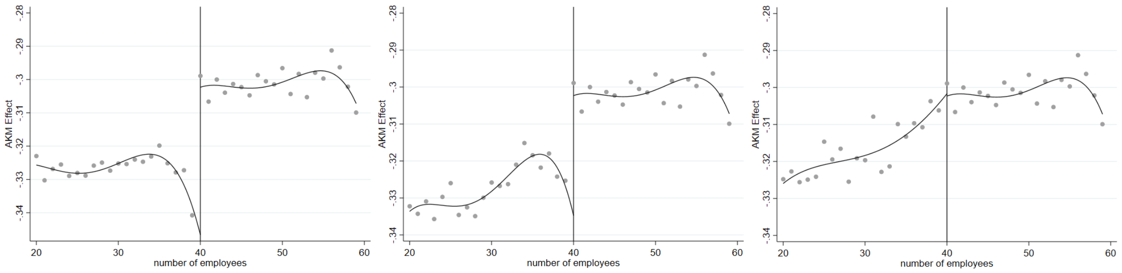
Figure B.5: Median Wages: Noncompliers, Perfect Compliers and Overcompliers



Noncompliers *Perfect Compliers* *Overcompliers*

Note: These graphs plot the ln of median wages by firm size around the threshold of 40 employees separately for *noncompliers*, *perfect compliers* and *overcompliers*. The black line approximates the functional form of the running variable (here with polynomial order fit p=4 and bandwidth h_{below}=20 and h_{above}=19).
Source: BsbM and BHP 2004–2011, own calculations.

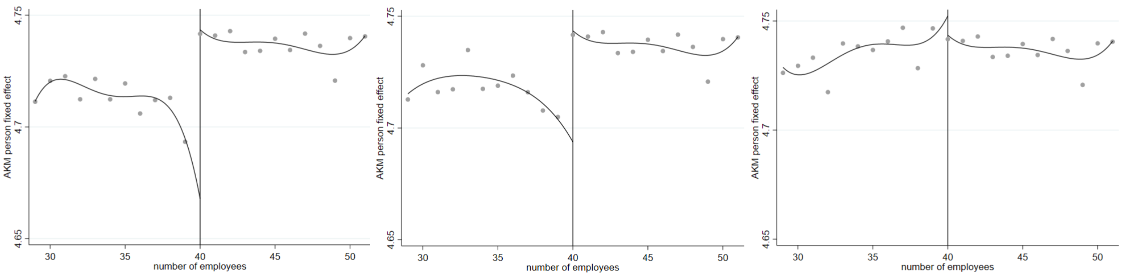
Figure B.6: Firm Productivity: Noncompliers, Perfect Compliers and Overcompliers



Noncompliers *Perfect Compliers* *Overcompliers*

Note: These graphs plot the AKM firm fixed effects by firm size around the threshold of 40 employees separately for *noncompliers*, *perfect compliers* and *overcompliers*. The black line approximates the functional form of the running variable (here with polynomial order fit p=4 and bandwidth h_{below}=20 and h_{above}=19).
Source: BsbM and BHP 2004-2010, own calculations.

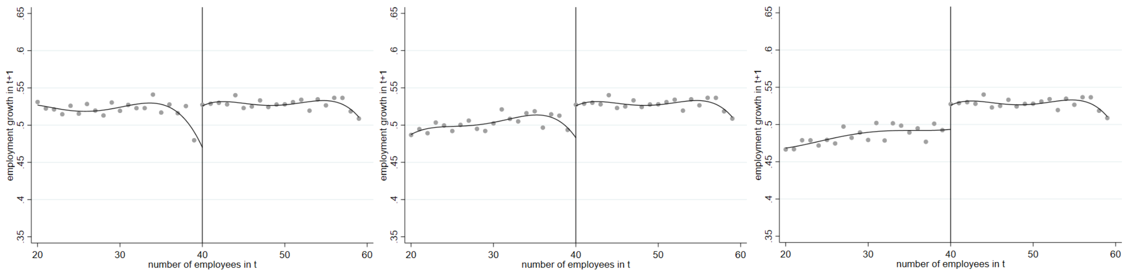
Figure B.7: Employee Productivity: Noncompliers, Perfect Compliers and Overcompliers



Noncompliers *Perfect Compliers* *Overcompliers*

Note: These graphs plot the AKM person fixed effects by firm size around the threshold of 40 employees separately for *noncompliers*, *perfect compliers* and *overcompliers*. The black line approximates the functional form of the running variable (here with polynomial order fit p=4 and bandwidth h_{below}=12 and h_{above}=12).
Source: BsbM and Integrated Employment Biographies 2010, own calculations.

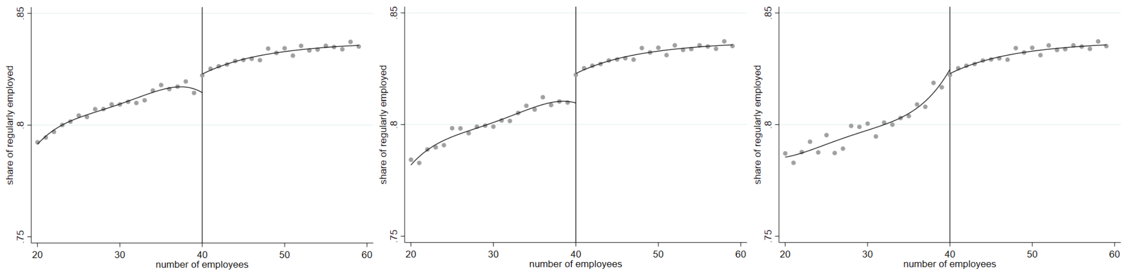
Figure B.8: Employment Growth: Noncompliers, Perfect Compliers and Overcompliers



Noncompliers *Perfect Compliers* *Overcompliers*

Note: These graphs plot employment growth by firm size around the threshold of 40 employees separately for *noncompliers*, *perfect compliers* and *overcompliers*. Employment growth is defined as a dummy variable equal to 1 if a firm has more employees (according to the BsbM) in t+1 than in t and equal to 0 otherwise. The black line approximates the functional form of the running variable (here with polynomial order fit p=4 and bandwidth h_{below}=20 and h_{above}=19).
Source: BsbM and BHP 2004–2011, own calculations.

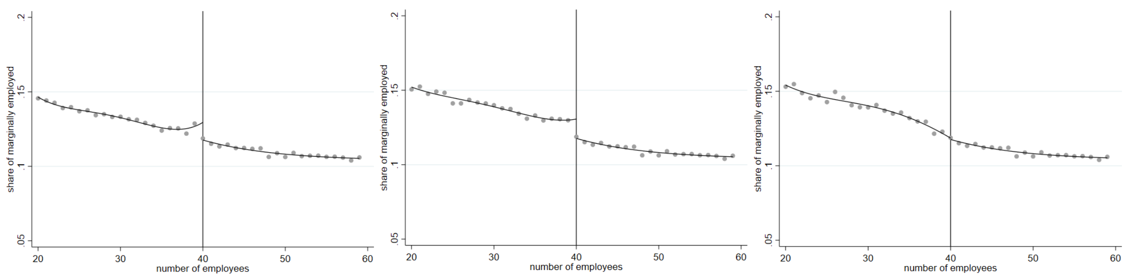
Figure B.9: Share of Regularly Employed Workers: Noncompliers, Perfect Compliers and Overcompliers



Noncompliers *Perfect Compliers* *Overcompliers*

Note: These graphs plot the share of regularly employed workers by firm size around the threshold of 40 employees separately for *noncompliers*, *perfect compliers* and *overcompliers*. The black line approximates the functional form of the running variable (here with polynomial order fit p=4 and bandwidth h_{below}=20 and h_{above}=19).
Source: BsbM and BHP 2004–2011, own calculations.

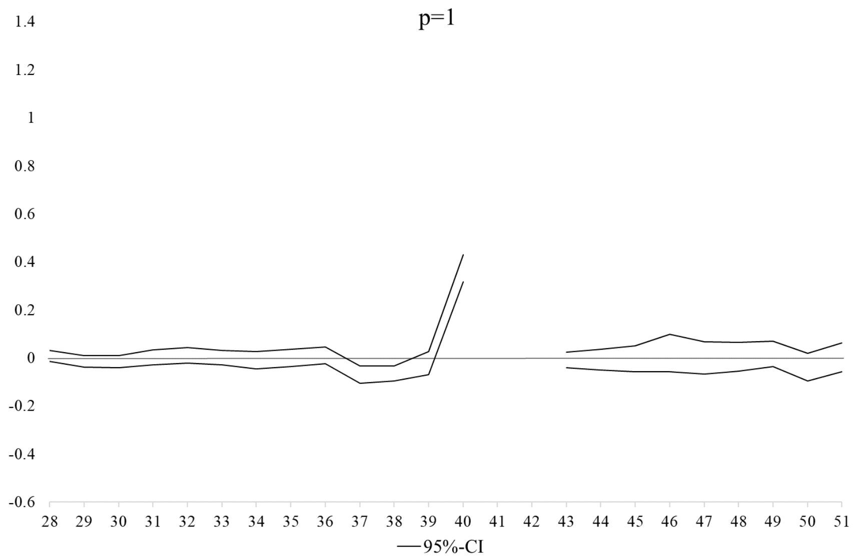
Figure B.10: Share of Marginally Employed Workers: Noncompliers, Perfect Compliers and Overcompliers



Noncompliers *Perfect Compliers* *Overcompliers*

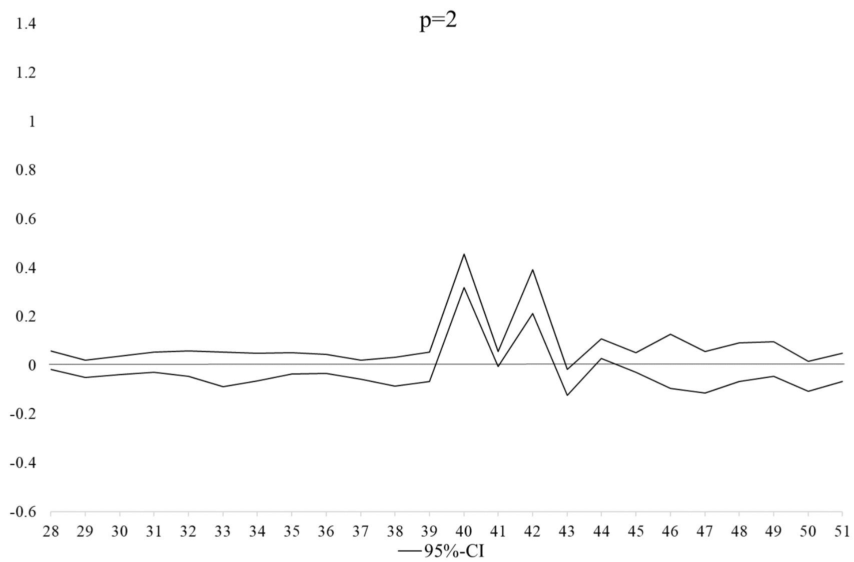
Note: These graphs plot the share of marginally employed workers by firm size around the threshold of 40 employees separately for *noncompliers*, *perfect compliers* and *overcompliers*. The black line approximates the functional form of the running variable (here with polynomial order fit p=4 and bandwidth h_{below}=20 and h_{above}=19).
Source: BsbM and BHP 2004–2011, own calculations.

Figure B.11: Placebo Thresholds (Polynomial Order 1)



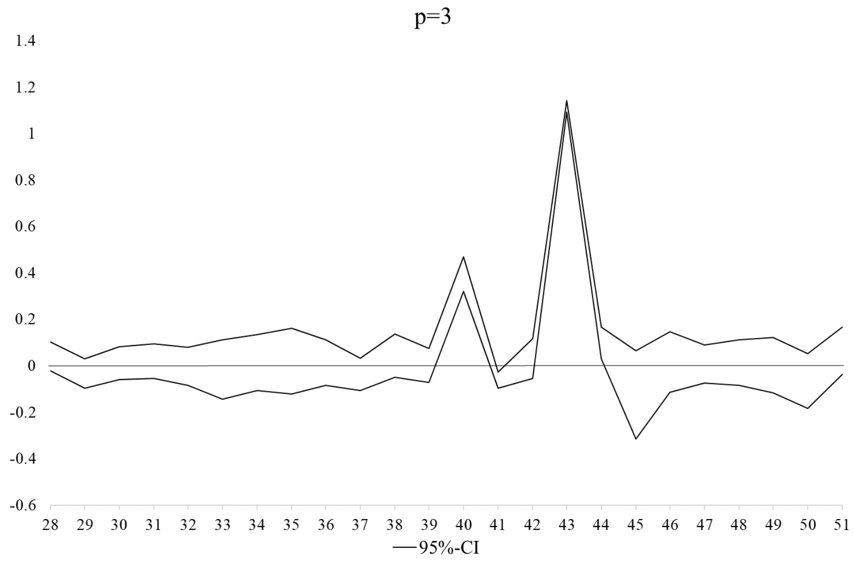
Note: This graph shows the effects of placebo thresholds on the mean number of disabled workers for polynomial order p=1 and an MSE-optimal bandwidth on either side of the threshold (estimated including predetermined covariates). All thresholds except the 40-employee threshold are placebo thresholds. The 95% confidence interval is the robust CI estimated with the *rdrobust* command in Stata. As the point estimates could fall outside the robust CIs, only the interval boundaries are shown. Standard errors are clustered at the firm level. For c=41 and c=42, there were not enough observations to perform MSE-optimal bandwidth calculations.
Source: BsbM and BHP 2004–2011, own calculations.

Figure B.12: Placebo Thresholds (Polynomial Order 2)



Note: This graph shows the effects of placebo thresholds on the mean number of disabled workers for polynomial order p=2 and an MSE-optimal bandwidth on either side of the threshold (estimated including predetermined covariates). All thresholds except the 40-employee threshold are placebo thresholds. The 95% confidence interval is the robust CI estimated with the *rdrobust* command in Stata. As the point estimates could fall outside the robust CIs, only the interval boundaries are shown. Standard errors are clustered at the firm level.
Source: BsbM and BHP 2004–2011, own calculations.

Figure B.13: Placebo Thresholds (Polynomial Order 3)



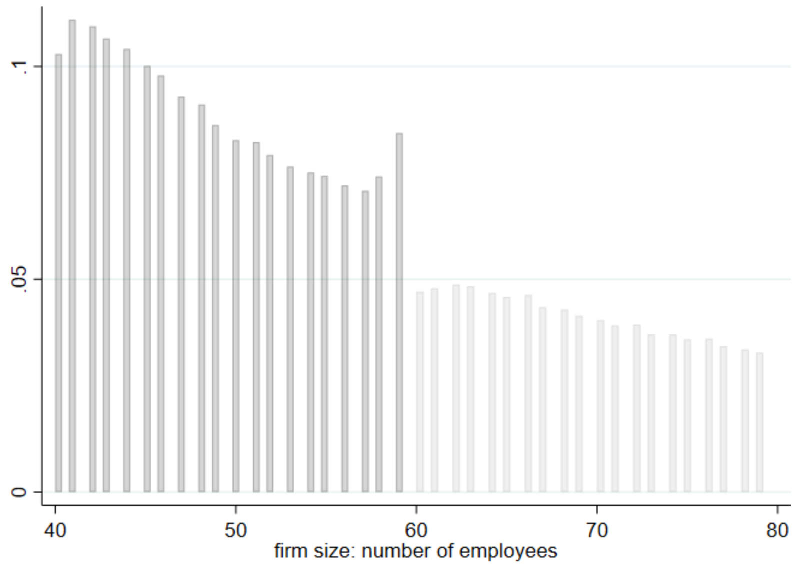
Note: This graph shows the effects of placebo thresholds on the mean number of disabled workers for polynomial order p=3 and an MSE-optimal bandwidth on either side of the threshold (estimated including predetermined covariates). All thresholds except the 40-employee threshold are placebo thresholds. The 95% confidence interval is the robust CI estimated with the *rdrobust* command in Stata. As the point estimates could fall outside the robust CIs, only the interval boundaries are shown. Standard errors are clustered at the firm level.
Source: BsbM and BHP 2004–2011, own calculations.

Table B.4: Cattaneo et al. Estimator Test Statistics - 60-Employee Threshold

	T		P > |T|
Robust	-22.5877		0.000
# of Observations		266,486	

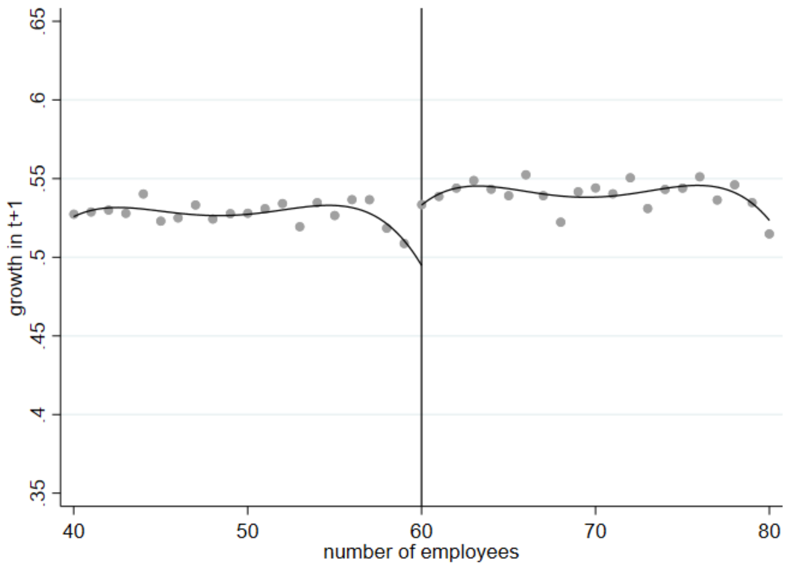
Source: BsbM and BHP 2004–2011, own calculations.

Figure B.14: Firm Size Density at the 60-Employee Threshold



Note: Histogram of firm size density around the threshold of 60 employees.
Source: BsbM and BHP 2004–2011, own calculations.

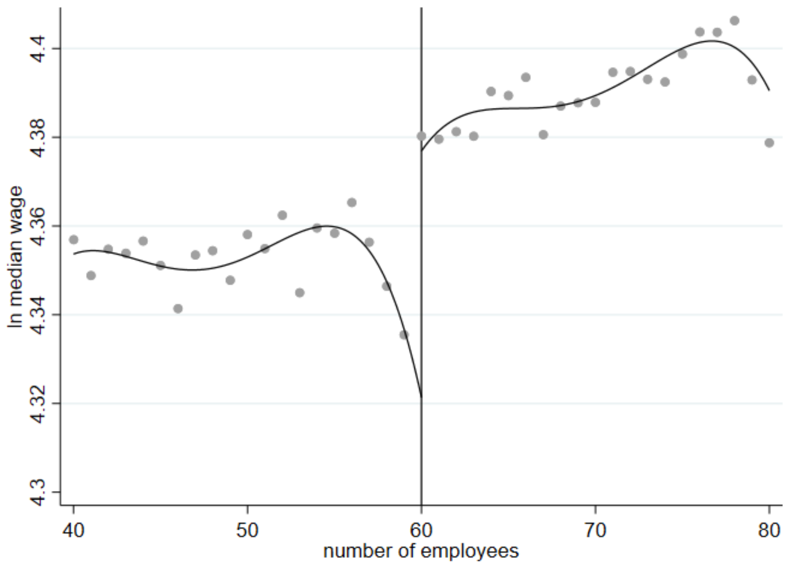
Figure B.15: Firm Dynamics



Growth

Note: This graph plots employment growth by firm size around the threshold of 60 employees. Employment growth is defined as a dummy variable equal to 1 if a firm has more employees (according to the BsbM) in t+1 than in t and equal to 0 otherwise. The black line approximates the functional form of the running variable (here with polynomial order fit p=4 and bandwidth h_{below}=20 and h_{above}=19).
Source: BsbM and BHP 2004–2011, own calculations.

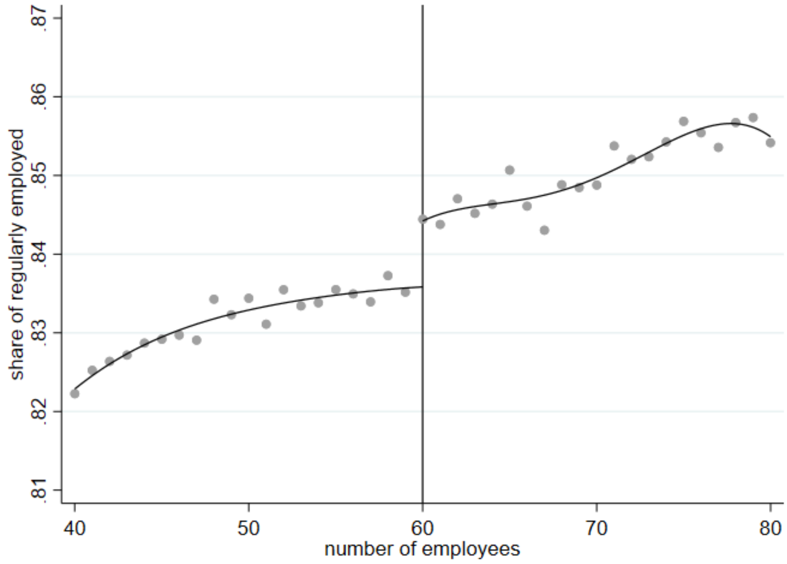
Figure B.16: Median Wages



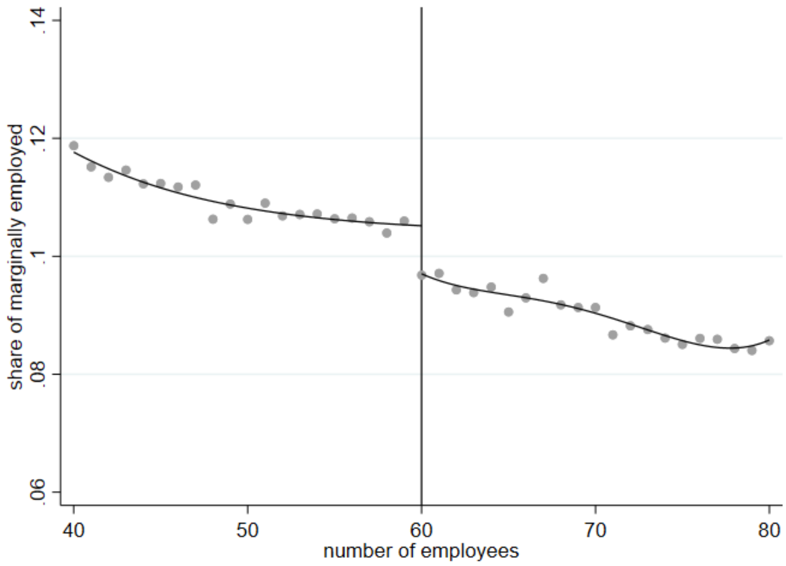
ln Median Wages

Note: This graph plots the ln of median wages by firm size around the threshold of 60 employees. The black line approximates the functional form of the running variable (here with polynomial order fit p=4 and bandwidth h_{below}=20 and h_{above}=19).
Source: BsbM and BHP 2004–2011, own calculations.

Figure B.17: Regular and Marginal Employment



(A) Share of Regularly Employed Workers



(B) Share of Marginally Employed Workers

Note: These graphs plot (A) the share of regularly employed workers and (B) the share of marginally employed workers by firm size around the threshold of 60 employees. The black line approximates the functional form of the running variable (here with polynomial order fit p=4 and bandwidth h_{below}=20 and h_{above}=19).
Source: BsbM and BHP 2004–2011, own calculations.

Table B.5: Bunching Behavior – 60-Employee Threshold

Dependent Variable	p = 1 (1) Total	p = 4 (2) Total	(3) Non-compliers	(4) Under-compliers	(5) Perfect Compliers	(6) Over-compliers
Sociodem. Structure						
Females	0.001	0.001	-0.003	-0.001	0.038	-0.019
Germans	0.003*	0.000	0.014	-0.016	0.003	-0.012
Employment Structure						
Median Wages (ln)	0.048***	0.050	0.090***	0.045	-0.029	0.010
Regularly Employed	0.009***	0.012*	0.025	-0.007	0.039*	0.006
Marginally Employed	-0.009***	-0.014**	-0.033*	-0.007	-0.019	0.002
Apprentices	-0.001	0.000	-0.002	0.007	-0.003	-0.009
Full-Time Workers	0.002	0.008	-0.005	-0.007	0.042	0.023
Part-Time Workers	0.007***	0.002	0.026	0.005	-0.013	-0.018
Skill Structure						
Low-Skilled Workers	-0.006***	-0.007	-0.009	0.000	-0.001	0.008
Medium-Skilled Workers	-0.001	-0.001	0.001	0.005	0.003	-0.005
High-Skilled Workers	0.010***	0.021	0.018	0.016	-0.012	-0.004
Firm Dynamics						
Growth	0.035**	0.031	0.120	0.069*	0.029	-0.315*

Notes: This table shows estimation results for the effects of the threshold of 60 employees on alternative outcome variables. *Noncompliers*, *undercompliers*, *perfect compliers* and *overcompliers* are firms below the threshold that employ zero, exactly one, exactly two or at least three disabled worker(s), respectively. All estimations are estimated by using the MSE-optimal bandwidth on either side of the threshold. Standard errors are clustered at the firm level. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels.
Source: BsbM and BHP 2004–2011, own calculations.

Table B.6: Robustness Test Excluding Public Administration Firms

		40-Employee Threshold – Bunching Effects			
	(1)	(2)	(3)	(4)	(5)
Coefficient		-1.339***	-1.488***	-1.940**	-2.025
Robust CI		[-2.348; -0.561]	[-2.725; -0.492]	[-4.033; -0.177]	[-5.769; 1.814]
Bandwidth h		6.23; 7.32	8.34; 9.79	8.07; 10.89	8; 10
Polynomial Order p		2	3	4	4
# of Observations		14	18	19	17
		40-Threshold – Threshold Effects			
	(1)	(2)	(3)	(4)	(5)
Coefficient	0.341***	0.373***	0.385***	0.394***	0.387***
Robust CI	[0.312; 0.428]	[0.314; 0.463]	[0.316; 0.473]	[0.299; 0.497]	[0.186; 0.667]
Bandwidth h	2.21; 3.54	4.08; 5.91	6.54; 8.02	8.36; 10.13	8; 10
Polynomial Order p	1	2	3	4	4
Covariates Included	yes	yes	yes	yes	yes
# of Observations	65,102	110,242	163,744	210,444	218,977
Lower Bound of Threshold Effect					0.149

Notes: This table shows the estimation results for the bunching effects (dependent variable: firm size density in %) and the threshold effects (dependent variable: mean number of disabled workers in a firm around the 40-employee threshold) without public administration firms. Basic covariates include firm age, regional characteristics (federal state) and industry. Standard errors are clustered at the firm level. ** and *** denote statistical significance at the 5% and 1%-level.
Source: BsbM and BHP 2004–2011, own calculations.

Table B.7: Robustness Test Excluding Multiestablishment Firms I

	40-Employee Threshold – Bunching Effects				
	(1)	(2)	(3)	(4)	(5)
Coefficient		-1.307***	-1.455***	-2.013**	-2.018
Robust CI		[-2.199; -0.607]	[-2.584; -0.538]	[-4.075; -0.221]	[-5.509; 1.725]
Bandwidth h		6.37; 7.20	8.34; 10.08	7.95; 11.05	8; 9
Polynomial Order p		2	3	4	4
# of Observations		14	19	19	16
	40-Employee Threshold – Threshold Effects				
	(1)	(2)	(3)	(4)	(5)
Coefficient	0.345***	0.371***	0.383***	0.390***	0.383***
Robust CI	[0.316; 0.427]	[0.316; 0.452]	[0.317; 0.466]	[0.297; 0.489]	[0.190; 0.678]
Bandwidth h	2.23; 3.36	4.19; 5.36	6.56; 7.61	8.24; 9.45	8; 9
Polynomial Order p	1	2	3	4	4
Covariates included	yes	yes	yes	yes	
# of Observations	76,005	128,795	182,109	237,516	209,599
Lower Bound of Threshold Effect					0.198

Notes: This table shows the estimation results for the bunching effects (dependent variable: firm size density in %) and the threshold effects (dependent variable: mean number of disabled workers in a firm around the 40-employee threshold) without identifiable multiestablishment firms. Basic covariates include firm age, regional characteristics (federal state) and industry. Standard errors are clustered at the firm level. ** and *** denote statistical significance at the 5% and 1% levels.
Source: BsbM and BHP 2004–2011, own calculations.

Table B.8: Robustness Test Excluding Multiestablishment Firms II

	(1)	(2)	(3)	(4)	(5)
	p = 1			p = 4	
Dependent Variable	Total	Total	Noncompliers	Perfect Compliers	Overcompliers
Sociodemographic Structure					
Share of Females	-0.003	-0.011	-0.006	-0.017	-0.011
Share of Germans	0.005***	0.012*	0.022**	0.005	-0.000
Employment Structure					
Median Wages (ln)	0.050***	0.085***	0.095***	0.045*	0.027
AKM Firm Fixed Effects	0.029***	0.050***	0.048***	0.037**	0.020
AKM Person Fixed Effects	0.039***	0.033***	0.048***	0.043	-0.004
Share of Regularly Employed	0.014***	0.016***	0.019***	0.016*	0.007
Share of Marginally Employed	-0.015***	-0.024***	-0.037***	-0.015*	-0.004
Share of Apprentices	0.000	0.002	0.009	-0.003	-0.001
Share of Full-Time Workers	0.008**	0.015	0.012	0.024*	0.018
Share of Part-Time Workers	0.003	0.007	0.014	-0.005	-0.005
Skill Structure					
Share of Low-Skilled Workers	-0.005***	-0.010	-0.015	-0.010	0.002
Share of Medium-Skilled Workers	-0.003	0.006	0.016	0.005	-0.021
Share of High-Skilled Workers	0.009***	0.007	0.003	0.003	0.018
Firm Dynamics					
Employment Growth in t+1	0.071***	0.228***	0.354***	0.118*	.0263

Notes: This table shows the estimation results for the effect of the threshold of 40 employees on alternative outcome variables. *Noncompliers*, *perfect compliers* and *overcompliers* are firms below the threshold that employ zero, exactly one or at least two disabled worker(s), respectively. All estimations are estimated by using the MSE-optimal bandwidth on either side of the threshold. Standard errors are clustered at the firm level. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels.
Source: BsbM and BHP 2004–2011 (2004-2010 for AKM firm fixed effects), own calculations.

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