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The Pros and Cons of Sick Pay Schemes: Testing for Contagious Presenteeism and Shirking Behavior*

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Abstract

This paper proposes a test for the existence and degree of contagious presenteeism and negative externalities in sickness insurance schemes. First, we theoretically decompose moral hazard into shirking and contagious presenteeism behavior and derive testable conditions. Then, we implement the test exploiting German sick pay reforms and administrative industry-level data on certified sick leave by diagnoses. The labor supply adjustment for contagious diseases is significantly smaller than for non-contagious diseases. Lastly, using Google Flu data and the staggered implementation of US sick leave reforms, we show that flu rates decrease after employees gain access to paid sick leave.

JEL Classification: I12; I13; I18; J22; J28; J32

Keywords: sickness insurance, paid sick leave, presenteeism, contagious diseases, infections, negative externalities, shirking, US, Germany

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"Send me a bill that gives every worker in America the opportunity to earn seven days of paid sick leave. It's the right thing to do. It's the right thing to do."

Barack Obama
in his State of the Union Address (January 20, 2015)

"I think the Republicans would be smart to get behind it."

Bill O'Reilly
in The O'Reilly Factor – Fox News (January 21, 2015)

1 Introduction

A major economic justification for publicly provided access to paid sick leave is "presenteeism" and negative externalities in case of contagious diseases. When workers lack access to paid sick leave, they may go to work despite being sick. Going to work despite being sick is commonly referred to as "presenteeism." Particularly in professions with direct customer contact, presenteeism in case of contagious diseases unambiguously leads to negative externalities and infection spillovers for co-workers and customers. Given the low influenza vaccination rates of around 40% in the US and 10% to 30% in the EU (Blank et al., 2009; Centers for Disease Control and Prevention, 2014a), workplace presenteeism is one important channel through which infectious diseases spread. After the first occurrence of flu sickness symptoms, humans are contagious for 5 to 7 days (Centers for Disease Control and Prevention, 2014b). Over-the-counter (OTC) drugs that suppress symptoms, but not contagiousness, promote the spread of disease in cases of presenteeism and non-insured workplace absenteeism (Earn et al., 2014). Worldwide, seasonal influenza epidemics alone lead to 3 to 5 million severe illnesses and an estimated 250,000 to 500,000 deaths; in the US, flu-associated annual deaths range from 3,000 to 49,000 (World Health Organization, 2014; Centers for Disease Control and Prevention, 2014b).

Historically, paid sick leave was actually one of the first social insurance pillars worldwide; this policy was included in the first federal health insurance legislation. Under Otto van Bismarck, the *Sickness Insurance Law of 1883* introduced social health insurance which included 13 weeks of paid sick leave along with coverage for medical bills. The costs associated with paid sick leave initially made up more than half of all program costs, given the limited availability of expensive medical treatments in the 19^{th} century (Busse and Riesberg, 2004). Other European countries followed quickly and, today, virtually every European country has some form of universal access to paid sick leave—with varying degrees of generosity.

Opponents of universal paid sick leave point to the fact that such social insurance systems would encourage shirking behavior and reduce labor supply. Moreover, forcing employers to provide sick pay via mandates or new taxes would dampen job creation and hurt employment. A final argument against government mandated paid sick leave states that, when coverage is optimal, the private market would ensure that employers voluntarily provide such benefits.

The US is the only industrialized country worldwide without universal access to paid sick leave (Heymann et al., 2009). Half of all American employees have no access to paid sick leave, particularly low-income and service sector workers (Lovell, 2003; Boots et al., 2009; Susser and Ziebarth, 2015). However, in the US, support for sick leave mandates has grown substantially in the last decade: On the city level, sick leave schemes have been implemented, among others, in the cities of San Francisco, Washington D.C., Seattle, Philadelphia, and New York City. On the state level, Connecticut was the first state to introduce a sick leave scheme in 2012 (for service sector workers in non-small businesses). California, Massachusetts, and Oregon followed in 2015. At the federal level, reintroduced in Congress in March 2013, the *Healthy Families Act* foresees the introduction of universal paid sick leave for up to seven days per employee and year. The epigraphs above clearly demonstrate the support not only among Democrats but conservatives alike.

As discussed, one economic argument for paid sick leave hinges crucially on the existence of negative externalities and presenteeism with regard to contagious diseases. Despite being of tremendous relevance, empirically proving the existence of presenteeism with contagious diseases is extremely difficult, if not impossible, because contagiousness is generally unobservable. Several empirical papers evaluate the causal effects of cuts in sick pay, and find that employees adjust their labor supply in response to such cuts (Johansson and Palme, 1996, 2005; Ziebarth and Karlsson, 2010; De Paola et al., 2014; Ziebarth and Karlsson, 2014; Dale-Olsen, 2014; Fevang et al., 2014).[1] Traditionally, behavioral adjustments to varying levels of insurance generosity is labeled 'moral hazard' in economics (Pauly, 1974, 1983; Arnott and Stiglitz, 1991; Nyman, 1999; Newhouse, 2006; Felder, 2008; Bhattacharya and Packalen, 2012). However, in the case of sick leave, being able to disentangle shirking behavior from presenteeism is crucial in order to derive valid policy conclusions.

The main objective of this paper is to decompose moral hazard and to develop an approach to (indirectly) test for the existence of shirking, contagious presenteeism and associated negative externalities in workplace settings under sickness insurance coverage. To our knowledge, this paper is the first in the economic literature to define and test for the existence of contagious presenteeism.

[1]Other papers in the literature on sickness absence looked at and decomposed general determinants (Barmby et al., 1994; Markussen et al., 2011), investigated the impact of probation periods (Riphahn, 2004; Ichino and Riphahn, 2005), culture (Ichino and Maggi, 2000), gender (Ichino and Moretti, 2009), income taxes (Dale-Olsen, 2013), and unemployment (Askildsen et al., 2005; Nordberg and Røed, 2009; Pichler, 2015). There is also research on the impact of sickness on earnings (Sandy and Elliott, 2005; Markussen, 2012).

Although related and sometimes combined in laws, sick pay schemes differ crucially from maternity leave schemes (Gruber, 1994; Ruhm, 1998; Waldfogel, 1998; Rossin-Slater et al., 2013; Lalive et al., 2014; Carneiro et al., 2015; Thomas, 2015) due to *(i)* the negative externalities induced by contagious presenteeism in combination with *(ii)* information asymmetries between employers and employees about the type and extent of the employee's disease. One key element of the proposed theoretical mechanism is private information about the type of disease that workers contract. Supported by intuition and empirical evidence (Pauly et al., 2008), employers have only incomplete information about employees' contagiousness and do not fully internalize the negative externalities induced by the spread of contagious diseases to co-workers and customers. Sick pay schemes incentivize contagious employees to stay at home but also induce non-contagious employees to shirk.

Accordingly, the first part of the paper develops an economic model that decomposes moral hazard into shirking and contagious presenteeism. According to our theoretical framework, the negative externalities can be quantified by assessing changes in infections after changes in sick pay. The model predicts that changes in sick pay generosity induce changes in the two undesired behaviors that work in opposite directions: shirking and contagious presenteeism. We explicitly refrain from a normative welfare analysis which would require to weight these two phenomena, depending on societal preferences. We rather provide a positive analysis and the first approach to theoretically define and empirically measure these countervailing effects. Note that the theory and empirical sections do not hinge on whether the sick pay scheme is mandated by the government or not.

The second part of the paper exploits two German policy reforms which varied the level of sick pay. Using administrative data aggregated at the industry level and variation in industry-specific sick pay regulations, sick pay cuts from 100 to 80% of foregone wages reduced overall sickness rates by about 20%. This is in line with the standard predictions of our model and the previous literature (Johansson and Palme, 1996, 2005; Ziebarth and Karlsson, 2010; De Paola et al., 2014; Ziebarth and Karlsson, 2014; Fevang et al., 2014). Next, and more importantly, we analyze the labor supply effects by certified disease categories. In line with the theoretical model implications, we find disproportionately large labor supply adjustments for musculoskeletal diseases ("back pain"). Meanwhile, the labor supply adjustments in case of infectious diseases are significantly smaller. According to our model, the differences between the small labor supply effects for contagious diseases and the large labor supply effects for non-contagious diseases are a function of additional infections due to contagious presenteeism. Additional infections increase sick leave rates of infectious diseases and countervail decreases due to lower sick pay. Thus, when mandated sick pay is lowered, policymakers have to consider the trade-off between *(i)* the short-run effect of a reduction in shirking vs. *(ii)* an increase in contagious presenteeism leading to *(iii)* a higher infection rate and more relapses in the medium-run.

The third part of the paper utilizes high frequency Google Flu data to evaluate the impact of US sick pay schemes on influenza rates. The staggered implementation of several sick pay schemes at the regional level in the US naturally leads to the estimation of standard difference-in-differences models. Although the US sick pay schemes vary in their comprehensiveness, and some have exemptions reducing the effectiveness of lowering infection rates, we can show the following: When US employees gain access to paid sick leave, the general flu rate in the population decreases by about 10%. This finding yields additional strong evidence for the existence of contagious presenteeism. Moreover, it shows that a reduction in contagious presenteeism occurs when sick pay coverage increases, resulting in less infections and lower influenza activity. This paper is one of the first to study the introduction of sick pay mandates in the US (Ahn and Yelowitz (2015) being one exception). In addition, it is one of the first economic papers to exploit high frequency data from Google Flu Trends, a rich dataset that assesses influenza activity on a weekly basis starting from 2003.

Obviously, this paper is close in spirit to papers that estimate causal labor supply effects of changes in sick pay levels (Johansson and Palme, 1996, 2002, 2005; Ziebarth, 2013; Ziebarth and Karlsson, 2010, 2014). However, none of these papers estimates labor supply effects by disease groups. In particular, this paper extends the small economic literature on presenteeism at the workplace (Aronsson et al., 2000; Chatterji and Tilley, 2002; Brown and Sessions, 2004; Pauly et al., 2008; Barmby and Larguem, 2009; Johns, 2010; Böckerman and Laukkanen, 2010; Markussen et al., 2012; Pichler, 2015; Hirsch et al., 2015; Ahn and Yelowitz, 2015). With one exception, none of the empirical studies on presenteeism just cited identifies or intends to identify causal effects of sick leave schemes on presenteeism. The exception is Markussen et al. (2012) who study the impact of partial absence certificates on what they label 'presenteeism.' However, they define presenteeism very broadly—as a general increase in labor supply when activation requirements become tighter. Pauly et al. (2008) ask 800 US managers about their view on employee presenteeism with *(a)* chronic and *(b)* acute diseases. Pichler (2015) provides evidence for the hypothesis that presenteeism is procyclical due to a higher workload during economic booms. Barmby and Larguem (2009) exploit daily absence data from a single employer and estimate absence determinants as well as transmission rates of contagious diseases, linking the estimation approach nicely to an economic model of absence behavior.

Finally, this paper also adds to the literature on the determinants and consequences of epidemics and vaccinations (cf. Mullahy, 1999; Bruine de Bruin et al., 2011; Uscher-Pines et al., 2011; Ahn and Trogdon, 2015). For example, Maurer (2009) models supply and demand side factors of influenza immunization, whereas Karlsson et al. (2014) empirically assess the impact of the 1918 Spanish Flu on economic performance in Sweden.

The next section discusses our economic model and derives testable conditions under presenteeism and contagious diseases. Section 3 first explains the German policy reforms to be studied and the data used. Then the empirical approach leads to the estimation of the theoretical model. Section 4 follows this structure for the US, and Section 5 concludes.

2 Identifying Contagious Presenteeism and Negative Externalities

2.1 Modeling Shirking and Contagious Presenteeism Behavior

We extend and build upon a mix of standard work-leisure models to theoretically study the absence behavior of workers (cf. Brown, 1994; Barmby et al., 1994; Brown and Sessions, 1996). While additional arguments for or against the provision of sick pay exist, our model focuses on the trade-off between shirking and presenteeism behavior and negative externalities, in form of infections, resulting from information asymmetries.[2] Since we construct a model of individual behavior we omit the i subscript in order to simplify notation. We specify the individual utility function as:

$$u_t = (1 - \sigma_t)c_t + \sigma_t l_t, \qquad with\ \sigma_t \in [0, 1], \tag{1}$$

where u_t represents the utility of a worker at time t, c_t stands for consumption and l_t for leisure. The current sickness level is σ_t, with larger values of σ_t representing a higher degree of sickness. Importantly, this parameter is private information of the worker and unknown by the firm.

In time periods with high levels of σ_t, i.e., when the worker is very sick, utility is mostly drawn from leisure or recuperation time rather than consumption. On the other hand, if the sickness level is relatively low, the worker attaches more weight to consumption as opposed to leisure.[3]

[2] In particular, we abstain from modeling the employer's side and effects on the firm level. This could include employer signaling (or adverse selection) effects, peer effects, or discrimination against identifiable unhealthy workers (e.g. obese workers). We also abstain from analyzing general equilibrium labor market effects.

[3] While our model focuses on sickness and sickness absence, in principle a high σ_t only indicates a temporary preference for leisure. This might not necessarily be related to sickness and associated recuperation time, but also to other factors, such as sickness of family members and recreational activities.

With h defining hours of contracted work, T the total amount of time available—and assuming that workers are not saving, but consuming their entire income from work w_t or sick pay s_t—one can write the indifference condition between working and (sickness) absence formally as:

$$(1-\sigma_t)s_t + \sigma_t T = (1-\sigma_t)w_t + \sigma_t(T-h). \tag{2}$$

In most countries sick pay is not a flat monetary amount but rather a replacement rate of the current wage. Hence we substitute sick pay with $s_t = \alpha_t w_t$ in the equation above (with $\alpha_t \in [0,1]$).[4] Moreover, workers are paid based on their average productivity and, approximating reality, we assume rigid wages and thus a time invariant wage level w. We can then calculate the indifference point $\sigma^*(\alpha_t)$ for a given replacement rate α_t:

$$\sigma^*(\alpha_t) = \frac{(1-\alpha_t)w}{(1-\alpha_t)w + h}. \tag{3}$$

Hence if $\sigma_t > \sigma^*(\alpha_t)$ workers will be absent, while they will be present if $\sigma_t < \sigma^*(\alpha_t)$. The latter can be thought of the "normal" state under which the great majority, 80 to 90% of all workers, fall every day. The value of $\sigma^*(\alpha_t)$ where workers are indifferent solely depends on *(i)* the amount of money workers lose while on sick leave, $(1-\alpha_t)w$, and *(ii)* the contracted amount of working hours h.

2.1.1 Two Types of Diseases and Negative Externalities Due to Contagious Presenteeism

Next, let us assume that two types of (mutually exclusive) diseases exist: *(i)* contagious diseases denoted by subscript c, e.g., flus and *(ii)* non-contagious diseases denoted by subscript n, e.g., back pain.[5] More precisely, we assume that at every point in time there exist three fractions of workers: a first share of workers $1-q-p_t$ who are healthy, a second share of workers q who are sick due to a non-contagious disease $\sigma_t = \sigma_{nt}$, and a third share of workers p_t who are sick due to a contagious disease $\sigma_t = \sigma_{ct}$. In the latter two cases, the actual size of the disutility created by the sickness σ_t is determined by the density function $f(\sigma)$. Thus, whereas the level of σ_t determines the decision of

[4] Notice that the wage may also include non-monetary benefits, such as more job security. For instance Scoppa and Vuri (2014) find that workers who are absent more frequently face higher risks of dismissal. Thus even in countries with nominally full replacement, in our model, this might translate to a replacement rate smaller than one due to future income opportunities and other costs and benefits.

[5] In principle non-contagious diseases represent a special case of contagious diseases, where infections are equal to zero. Moreover, (diseases with) relapses can also be considered as a special case of contagious diseases, where the level of contagiousness is fairly low, as individuals "infect" only themselves.

the worker to stay at home or not, this additional characteristic determines whether the disease is contagious or not.[6]

The share of workers being affected by a contagious disease p_t changes over time depending on infections in the previous period, as outlined below. On the other hand, the share of workers affected by non-contagious diseases q is time invariant which is why we omit the time index t.[7]

As mentioned, importantly, both the severity of the disease and the "disease type" drawn by the worker is private information and unobservable by the employer. This is an important, yet realistic, assumption and drives the main mechanism below. It allows us to abstract away from a hypothetical scenario where employers can unambiguously and always identify workers with contagious diseases and simply send them home to avoid infections. The private information assumption seems reasonable given that disease type and contagiousness are mostly unobservable for the employer and subject to very incomplete monitoring. Note that most infectious diseases are contagious for several days before definite symptoms are observable. The availability and popularity of OTC drugs suppressing disease symptoms reinforce the unobservability assumption (Earn et al., 2014). Also note that, for our model to work, it is not necessary to assume that employees know their disease type.

Given $\sigma^*(\alpha_t)$ and assuming a worker population of size one, we can now define the sick leave rate A_t as the share of individuals absent from work:

$$A_t = A_{ct} + A_{nt} = (p_t + q) \int_{\sigma^*(\alpha_t)}^{1} f(\sigma) d\sigma; \tag{4}$$

similarly, the share of workers present at work is given by

$$P_t = (1 - p_t - q) + (p_t + q) \int_{0}^{\sigma^*(\alpha_t)} f(\sigma) d\sigma. \tag{5}$$

Given the replacement rate α_t, a share of workers

$$\pi_t(\alpha_t) = p_t \int_{0}^{\sigma^*(\alpha_t)} f(\sigma) d\sigma \tag{6}$$

[6]We also assume that, conditional on being sick ($\sigma > 0$), the shares of disease types (p_t and q) are independent of the density of the sickness level $f(\sigma)$.

[7]Note that we abstract away from any competing risks since an increase in contagious diseases does not affect the share of individuals with a non-contagious disease. While substitution might take place, we assume it is of a small enough margin not to be considered here.

is contagious but present at work. We define $\pi_t(\alpha_t)$ as **contagious presenteeism**. One economic purpose of providing paid sick leave is to provide financial incentives for sick worker to call in sick, such that infections caused by contagious presenteeism are minimized.

As seen, the share of workers with contagious presenteeism behavior who transmit diseases to their co-workers and to customers equals $\pi_t(\alpha_t)$. Following a standard SIS (susceptible-infected-susceptible) endemic model,[8] the transmission of diseases via contagious presenteeism depends on three factors: *(a)* the share of contagious workers working (the infected) π_t, *(b)* the share of non-contagious individuals who can be infected (the susceptibles) $S_t = (1 - p_t - q) + q \int_0^{\sigma^*(\alpha_t)} f(\sigma)d\sigma$, and *(c)* the transmission rate of the disease which we denote with r.[9] Therefore the share of individuals with contagious diseases is an increasing function of these three elements, formally $p_t(\pi_t, S_t, r)$. Thus contagious workers who show up at the workplace trigger the negative externalities that sick pay schemes intend to minimize.

2.1.2 Severely Sick Workers, Shirkers, and the Definition of Moral Hazard

If $\sigma_t > \sigma^*(0)$, workers are too sick to work and would stay at home even if they had to completely forgo wage (the replacement rate was zero). In this case, the utility function approximates $u_t = \delta\sigma_t l_t$. This can be thought of as a state where people are either *(i)* lying in bed with extremely high fever and heavy, acute, flu symptoms (as an example for a contagious disease), or *(ii)* lying in bed after chemotherapy in case of cancer (as an example for a non-contagious disease). Empirically, one can estimate that about 3 to 5% of all workers fall into this category on a given day.[10]

When employees gain access to sick pay ($\alpha_t > 0$), there will be a share of workers who call in sick as a result of their sick pay (workers with $\sigma^*(\alpha_t) < \sigma_t < \sigma^*(0)$). These individuals would go to work, if there was no sick pay. However, because they have access to sick pay, it is rational for them to be absent from work. In the domain of non-contagious diseases, we refer to these workers as shirkers. The share of shirkers at any point in time and for a given sick pay replacement level α_t equals

$$\omega(\alpha_t) = q \int_{\sigma^*(\alpha_t)}^{\sigma^*(0)} f(\sigma)d\sigma \tag{7}$$

[8] The SIS model is the classic framework for mathematically analyzing contagious diseases and was first discussed in the medical literature by Ross (1916) and Kermack and McKendrick (1927).

[9] It is outside the scope of this paper to model the transmission rate of contagious diseases explicitly (cf. Philipson, 2000; Barmby and Larguem, 2009; Pichler, 2015).

[10] In Germany, on a given day, about 7% of the workforce are on sick leave (see Section 3.2).

As productivity is hard to measure in most settings, we do not model work productivity explicitly. However, for non-contagious diseases, lower productivity due to sickness mostly dominates sickness absence and zero work output. Formally, denote with $\delta(\sigma^*(0))$ the sickness-related productivity losses for workers that are just indifferent between going to work and staying at home at a replacement rate of zero. If worker utility and firm profits have similar weights, then as long as $\sigma^*(0)\alpha_t w > \delta(\sigma^*(0))$ work is preferred to sickness absence. This condition compares the consumption utility from sickness benefits with the productivity losses from a sick non-contagious worker. Sickness absence is preferred from a societal point of view only if the productivity losses or consumption utility losses due to sickness are very large. For the rest of the paper we assume that $\sigma^*(0)\alpha_t w > \delta(\sigma^*(0))$, and thus working is preferred to sickness absence for non-contagious diseases, as long as the disease is not too severe $\sigma_t < \sigma^*(0)$.

Finally, we define moral hazard as the sum of shirking individuals and individuals exhibiting contagious presenteeism [11]

$$\rho_t(\alpha_t) = \omega(\alpha_t) + \pi_t(\alpha_t). \tag{8}$$

Proposition 1. *Under a sick pay scheme and given the existence of contagious as well as non-contagious diseases, there exists a fraction of contagious workers π_t that engage in presenteeism. Contagious workers who go to work induce negative externalities because they infect co-workers and customers. Likewise, there exists a fraction of non-contagious workers who shirk, ω. Moral hazard, ρ_t, is the sum of shirking and presenteeism.*

Contagious and non-contagious diseases differ in that the former lead to contagious presenteeism and infections, increasing the probability of infections. This negative externality is one main economic justifications for sick pay. The extent of the negative externality depends on the contagiousness of the disease. Therefore, in the context of our model, presenteeism is not harmful per se, but rather the negative externalities triggered by contagious presenteeism.

Changes in Sick Pay and Moral Hazard: Intuitive and Graphical Representation

To simplify, we assume (without loss of generality) that sick pay is high in the base year ($t = 0$) and is exogenously cut after one year in $t = y_1$. Deriving the indifference condition in equation (3)

[11] Similar to Einav et al. (2013) moral hazard is strictly speaking not a hidden action in our context, since it is perfectly observable whether an employee is present or not. It is rather hidden information that employees have about their personal sickness level and their type of sickness.

yields $\frac{\partial \sigma^*(\alpha)}{\partial \alpha} < 0$. This means that a decrease in the replacement rate—as induced by the first German reform in 1996—increases σ^* and thus more workers work, i.e., the sick leave rate decreases.

Following a sick pay cut, work attendance increases and sick leave decreases. However, what is even more relevant is how contagious presenteeism and shirking behavior changes. It can easily be shown that *(i)* shirking decreases because $\sigma^*(\alpha_{y_1}) > \sigma^*(\alpha_0)$. Moreover, *(ii)* contagious presenteeism increases for the same reason. Thus it remains ambiguous what happens to overall moral hazard since the first component of moral hazard, contagious presenteeism, increases while the second component, shirking, decreases.

Proposition 2. *Given the existence of contagious as well as non-contagious diseases, a sick pay cut increases contagious presenteeism which induces negative externalities through infections of co-workers and customers. At the same time, a sick pay cut reduces the fraction of shirkers. A priori, the impact on moral hazard, defined as the sum of both behaviors, is ambiguous. Analogously, an increase in sick pay decreases contagious presenteeism and increases shirking behavior.*

[Insert Figure 1 about here]

Figure 1 shows a graphical representation of Proposition 2. Panel A depicts the situation for non-contagious diseases. Initially, the share of shirkers—indicated by the sum of the two dark gray areas—is quite large. However, as sick pay decreases, more workers with non-contagious illnesses come to work and the shirking rate decreases.

Panel B depicts the situation for contagious diseases. As sick pay decreases, contagious presenteeism increases, meaning more workers with contagious illnesses come to work. Because of additional infections, the share of individuals with a contagious disease, p_t, increases, as represented by the outward shift of the density function.

Changes in Sick Pay and Moral Hazard: Analytical Derivation

Non-Contagious Diseases. $\frac{A_{n0}-A_{nt}}{A_{n0}} = \beta_{nt}$ denotes the percentage change in the sick leave rate of non-contagious diseases, when sick pay decreases and after t time periods have passed. Thus β_{nt} represents the cumulative reform effect at time t, or formally

$$\beta_{nt} = \frac{1}{A_{n0}} \left(q \int_{\sigma^*(\alpha_0)}^{1} f(\sigma) d\sigma - q \int_{\sigma^*(\alpha_t)}^{1} f(\sigma) d\sigma \right) = \frac{1}{A_{n0}} \left(q \int_{\sigma^*(\alpha_0)}^{\sigma^*(\alpha_t)} f(\sigma) d\sigma \right). \tag{9}$$

In the case of non-contagious disease, the reduction in workplace absences is equal to the reduction in shirking when sick pay decreases. Thus we can write

$$\beta_{nt} = \frac{1}{A_{n0}} \left(\omega(\alpha_0) - \omega(\alpha_t) \right). \tag{10}$$

Contagious Diseases. Similarly $\frac{A_{c0}-A_{ct}}{A_{c0}} = \beta_{ct}$ denotes the percentage change in the sick leave rate of contagious diseases, when sick pay decreases and after t time periods.

$$\beta_{ct} = \frac{1}{A_{c0}} \left(p_0 \int\limits_{\sigma^*(\alpha_0)}^{1} f(\sigma)d\sigma - p_t \int\limits_{\sigma^*(\alpha_t)}^{1} f(\sigma)d\sigma \right). \tag{11}$$

This expression can be rewritten as

$$\beta_{ct} = \frac{1}{A_{c0}} \left(\left(\pi_0(\alpha_t) - \pi_0(\alpha_0)\right) - \left((p_t - p_0) \int\limits_{\sigma^*(\alpha_t)}^{1} f(\sigma)d\sigma \right) \right), \tag{12}$$

where the first element corresponds to the increase in contagious presenteeism due to the sick pay cut (and the corresponding decrease in the absence rate)—related to the initial share of workers with a contagious disease, p_0. The second element corresponds to the increase in the absence rate due to additional infections as a result of the increase in contagious presenteeism.

As described, additional infections increase the infection rate, p_t. As seen in ***Proposition 2***, more contagious workers work after sick pay is cut. Furthermore, as more non-contagious workers work as well, the number of susceptibles increases. Both effects result in more infections. Depending on the magnitude of newly infected individuals, the increase in sickness absence due to infections offsets the decrease due to additional contagious presenteeism, at least partly. For example, if—at the firm level—one additional worker exhibits contagious presenteeism due to a sick pay cut, then the net effect of the sick pay cut on the overall sick leave rate would be zero if this additional worker infected one additional co-worker who then called in sick.

Next, we contrast the two offsetting behavioral forces, where β_{ct} and β_{nt} can be rewritten as:

$$\beta_{ct} = \beta_{nt} - \frac{1}{A_{c0}} \left((p_t - p_0) \int\limits_{\sigma^*(\alpha_t)}^{1} f(\sigma)d\sigma \right) \tag{13}$$

Accordingly, the behavioral adjustments of the two disease groups, β_{ct} and β_{nt}, only differ by the share of newly infected individuals weighted by the share of workers on sick leave prior to the sick pay cut. Thus, under the existence of contagious presenteeism, it holds that $\beta_{nt} > \beta_{ct}$.

Finally, note that by definition $\beta_{nt} > 0$. However—in case of contagious diseases—the sign of β_{ct} is ambiguous. For a very contagious disease, β_{ct} might become negative. Therefore the sign of β_{ct} remains an empirical question which will be assessed below.

Hypothesis 1 *After a sick pay cut, the absence rate for non-contagious diseases ("shirking") decreases ($\beta_{nt} > 0$). The sign of the absence rate for contagious diseases, β_{ct}, remains ambiguous because additional absences due to new infections might outweigh the immediate decrease in the absence rate due to the sick pay cut. The difference $\beta_{nt} - \beta_{ct}$ indicates additional absences due to new infections.*

Finally, we denote the overall percentage change in the absence rate with $\beta_t = \frac{\Delta A}{A_0}$:

$$\beta_t = \frac{1}{A_0}\left((\omega(\alpha_0) - \omega(\alpha_t)) + (\pi_0(\alpha_t) - \pi_0(\alpha_0)) - \left((p_t - p_0) \int_{\sigma^*(\alpha_t)}^{1} f(\sigma) d\sigma \right) \right). \tag{14}$$

The next subsection discusses how these effects can be empirically identified in order to quantify the change in shirking and in new infections following a change in sick pay coverage.

2.2 Identifying Contagious Presenteeism and Negative Externalities Empirically

2.2.1 Using Disease-Specific Sick Leave Rates to Identify Contagious Presenteeism

Now assume data on sick leave behavior and sick pay schemes exist. Furthermore, assume a reform exogenously varied sick pay and one can identify different groups of affected workers. Then we can empirically estimate the causal effect of the change in sick pay on the share of workers who call in sick. In the notation above, we thus empirically identify β_t.

Moreover, assume that we could even empirically identify two different disease categories $_c$ and $_n$ and the share of workers who call in sick with certified sickness due to contagious and non-contagious diseases. Then one could carry out a statistical test to check if $\beta_{nt} > \beta_{ct}$. In other words, one could test if a sick pay cut induced decrease in sick leave is larger for disease categories $_n$ as compared to $_c$, which would yield evidence for an increased spread of contagious diseases via an increase in contagious presenteeism behavior.

Proposition 4a. *Given the existence of a reform that exogenously varied sick pay and sick leave data on differently affected employees, one can econometrically test if $\beta_t > 0$, i.e., if the labor supply adjustment with respect to a sick pay cut is positive and, if so, how large it is.*

Proposition 4b. *Given the availability of data for contagious and non-contagious sick leave rates, one can estimate β_{nt} and β_{ct}. The size of β_{nt} is informative for the relevance of shirking behavior. β_{ct} represents both the increase in contagious presenteeism and in additional sick leave due to infections triggered by contagious presenteeism behavior.*

Proposition 4c. *Lastly, one can econometrically test if $\beta_{nt} > \beta_{ct}$ (Hypothesis 1), i.e., whether the labor supply adjustment is larger for non-contagious than for contagious diseases and, and if so, how large the differential is. The size of the differential illustrates additional infections that lead to additional sick leave as a result of contagious presenteeism. These represent negative externalities under lower sick pay.*

Section 3 exploits German sick pay reforms and data on disease-specific sick leave rates to empirically identify shirking and contagious presenteeism behavior.

2.2.2 Using Population Influenza Rates to Identify Contagious Presenteeism

Now assume data on influenza activity from a large set of locations. Furthermore, assume that sick pay schemes were implemented in some of these locations. Our model then predicts that access to sick pay coverage reduces contagious presenteeism (***Proposition 2***). This leads to a reduction in the share of individuals infected by a contagious disease.

Assume there is no sick pay at time zero ($t = 0$), and that sick pay is introduced after one year ($t = y_1$). Then the reduction in contagious diseases at t, ϕ_t, can be defined as

$$\phi_t = (p_t - p_0) f(\sigma). \tag{15}$$

Given appropriate data on contagious disease incidences, one can empirically test whether $\phi_t < 0$; i.e., whether sick pay coverage reduces the incidence rate of infectious diseases in the population. $\phi_t < 0$ would yield strong empirical evidence for a reducion in contagious workplace presenteeism due to high sick pay.

Proposition 5a. *Given the existence of a reform that exogenously introduced sick pay as well as infectious disease data on differently affected populations, one can econometrically test if $\phi_t < 0$, i.e., if the incidence of infectious diseases decreases when employees gain access to sick pay and, if so, how large the reduction is.*

Proposition 5b. *The size of the differential, $\Delta\phi_t$, represents the decrease in infections as a result of a decrease in contagious workplace presenteeism. It represent the decrease in negative population externalities because of sick pay coverage.*

Section 4 exploits US sick pay reforms and data on influenza rates to empirically identify contagious presenteeism behavior and negative population externalities of minimal sick pay.

3 Evidence from German Sick Leave Reforms

3.1 The German Employer Sick Pay Mandate

Germany has one of the most generous universal sick leave systems in the world. The system is predominantly based on employer mandates. In Germany, employers are mandated to continue wage payments for up to six weeks per sickness episode. In other words, employers have to provide 100% sick pay from the first day of a period of sickness without benefit caps.

In the case of illness, employees are obliged to inform their employer immediately about both the sickness and the expected duration. From the fourth day of a sickness episode, a doctor's certificate is required. However, employers have the right to ask for a doctor's note from day one of a spell, and many employees voluntarily submit doctor's notes from day one.

If the sickness lasts more than six continuous weeks, the doctor needs to issue a different certificate. From the seventh week onwards, sick pay is disbursed by the health insurers (called "sickness funds") and lowered to 80% of foregone gross wages for those who are insured under Statutory Health Insurance (SHI).[12]

[12] In principle, there is no limit to the frequency of sick leave spells. However, if employees fall sick again due to the same illness after an episode of six weeks, the law explicitly states that they are only again eligible for employer-provided sick pay if at least six months have been passed between the two spells or twelve month have been passed since the beginning of the first spell. This paragraph intends to avoid substitution of long-term spells by short-term spells.

3.2 The Policy Reforms of 1996 and 1999

3.2.1 Sick Pay Cut at the End of 1996

In 1996, the center-right government passed a *Bill to Foster Growth and Employment*, effective October 1, 1996. Panel A of Table A1 in the Appendix summarizes how the bill altered the federal employer mandate. The most important provision of the bill reduced the minimum statutory sick pay level from 100% to 80% of foregone wages.[13] In addition to Table A1, Ziebarth and Karlsson (2010, 2014) provide more details on the regulatory changes and affected employee groups. This paper solely focuses on the implementation at the industry level among private sector employees who were covered by collective agreements.

Ongoing union pressure made employer associations in various industries—through collective agreements—to voluntarily provide sick pay on top of the statutory regulations. Further, the question of whether employees in specific industries were entitled to claim 100% or 80% of their salary during sickness episodes was determined by existing collective agreements and their legal interpretation. Some existing agreements explicitly, but probably coincidentally, stated that sick pay would be 100%, while others did not mention sick pay at all. In the former case, sick pay would remain 100% despite the decrease in the generosity of the employer mandate, whereas in the latter case, sick pay would decrease to 80% until a revised agreement was negotiated.

Review of Collective Agreements. We reviewed all collective agreements that existed during the time of the sick pay reforms and categorized industries. Overall, one can distinguish three different groups and industries: Panel B of Table A1 provides the provisions at the industry level and our categorization.

Group I is composed of the construction sector, whose collective agreement covered about 1.1 million private sector workers. When the law was passed in 1996, the existing collective agreement did not include any explicit provision on sick pay, which is why the entire federal regulations applied to the construction sector at the time of the bill's implementation. A negotiated compromise between unions and employers resulted in a new agreement which became effective July 1, 1997. This new agreement specified that the cut in the replacement rate would only be applied during the first three days of a sickness episode.[14]

[13]In addition to this bill, another bill cut SHI long-term sick pay from the seventh week onwards from 80% to 70% of forgone gross wages. Ziebarth (2013) shows that this second bill did not induce significant behavioral reactions among the long-term sick.

[14]In 1997 a minimum wage in the construction sector was introduced. Theoretically a wage increase should also lead to a reduction in sickness absence. However, Blien et al. (2009) and Rattenhuber (2011) only find small effects in East Germany which are no threat to the application of our method and the general empirical findings.

Group II counts at least 4.4 million covered employees and is quantitatively the largest group. It includes eleven industries as specified in the notes to Table A1, among them the steel, textile and automobile industry. Union leaders in these industries managed to maintain the symbolically important 100% sick pay level. However, in return, they agreed to exclude paid overtime from the basis of calculation for sick pay, which effectively means that employees with a significant amount of overtime hours experienced sick pay cuts.[15]

Group III is composed of seven industries, all of which stated in their collective agreements that they would maintain 100% sick pay. Moreover, in contrast to **Group II**, these industries did *not* exclude overtime payments from the basis of calculation. Hence the 4 million employees covered by these agreements serve as control group in the evaluation of the 1997 sick pay cut.

3.2.2 Reversal of Main Sick Pay Cut 1999 and Remaining Changes

After the federal election was won by the new center-left coalition in 1998, as a reaction to the 1996 bill, the *Bill for Social Insurance Corrections and to Protect Employee Rights* was passed and became effective January 1, 1999. It increased federally mandated sick pay again from 80% to 100%. However, as Table A1 illustrates, while the main provision was reversed, two minor—but potentially important—details made the new arrangements less generous than sick pay coverage prior to October 1996. And in combination with the meanwhile negotiated collective agreements, they affected the three groups in Table A1 differently.

First, the four week waiting period—introduced in October 1996—was maintained. However, to our knowledge no collective agreement had excluded the application of this waiting period, meaning that none of the three groups was affected by this provision in 1999. Second, the 1999 bill explicitly stated that paid overtime would be excluded from the basis of calculation. This provision was not part of the 1996 reform bill. It was probably a reaction to the many collective agreements that had implemented such a provision at the industry level in 1997 and 1998. However, because no industry

[15] There are several reasons why this type of sick pay decrease may be of minor relevance: *(a) Fraction of Employees Effectively Affected.* As representative SOEPGroup (2008) data show, among BKK insurees (which our main dataset is composed of), only 19% had paid overtime hours in 1998, the average being 4 hours per week. *(b) Size of Cut.* Whereas a decrease in the base rate to 80% would reduce net sick pay by €280 per month (in 1998 values), the exclusion of paid overtime would only lead to a net cut of €110 per month, conditional on working overtime and getting paid for it. *(c) Salience of Cut.* While maintaining the 100% replacement level had a high symbolic meaning for unions, the indirect reductions in sick pay were not communicated as openly, and it is questionable if every employee was aware of them. *(d) Affected individuals.* One could suspect that employees with paid overtime hours might be highly motivated employees in leading positions with a low number of sick days and a low propensity to shirk. However, as the SOEP shows, employees with paid overtime had on average 10 sick days per year while those *without* paid overtime hours had only 4.7 sick days.

in Group I and III of Table A1 excluded paid overtime voluntary in their 1997/1998 agreements, ironically, **Group III**'s sick pay became *less* generous as a result of the 1999 center-left bill.

Thus, when evaluating the 1999 reform, **Group II** serves as the main control group that did not experience any changes in their sick pay scheme between 1997/1998 and 1999. **Group III** was treated; their sick pay scheme became *less* generous due the exclusion of paid overtime from the basis of calculation.[16] Again, as in 1996, **Group I** serves as the main treatment group whose sick pay level was here increased from 80% to 100%.

3.3 Exploiting Administrative Data on Disease-Specific Sickness Absence: 1994-2004

In Germany, information on certified sickness absence—including diagnoses—are collected by the 124 non-profit SHI sickness funds covering 90% of the population (*Gesetzliche Krankenversicherungen (GKV)*). In 1995, before the first reform, switching between health plans was not possible and employees were assigned to company-based health plans (*Betriebskrankenkassen, BKKs*) if their employer offered such plans (similar to the employer-sponsored health plans in the US but with mandatory enrollment). In 1995, a total of 960 SHI sickness funds existed, and 690 or 72% of them were company-based health plans (German Federal Statistical Office, 2014). Employees covered by these health plans were likely also covered by binding collective agreements. Eibich et al. (2012); Schmitz and Ziebarth (2015) provide more details on the German health insurance system].

The Federal Association of Company-Based Sickness Funds (*BKK Dachverband*) annually publishes sick leave statistics of their 4.8 million enrollees (19% of all private sector employees) who are mandatorily SHI insured and gainfully employed (Bundesverband der Betriebskrankenkassen (BKK), 2004).[17] The *Krankheitsartenstatistik* reports both the incidence as well as the length of sickness spells by gender, age group, ICD diagnoses, and industry. We collected and digitized information from annual reports between 1994 and 2004.[18] The descriptive statistics are in the Appendix, Table A2.

[16] In the 1996 reform, **Group II** and **Group III** had reverse roles—Group II was treated with overtime exclusion and Group III the control group. This should be kept in mind when interpreting the signs of the coefficient estimates.

[17] Although, strictly speaking, BKKs are not legally obliged to contribute to the *Krankheitsartenstatistik*, the overwhelming majority does, probably simply out of tradition to contribute to this important statistic that has been existing since 1976. In 2013, more than 90% of all mandatorily insured BKK enrollees were covered by the *Krankheitsartenstatistik* (Bundesverband der Betriebskrankenkassen (BKK), 2004; German Federal Statistical Office, 2014). There is no evidence that this share systematically varied due to the reforms.

[18] We cannot use earlier data due to a lack of consistency that goes back to an earlier reform. Although the data contain information on the duration of sickness spells by disease groups, we decided to not exploit this information as the theoretical predictions of the reforms on the duration of spells are ambiguous.

In total, we count 1,188 observations, where each observation represents one industry and year as well as the diagnosed sickness category. More specifically, we count 11 years and 18 industries which adds up to 198 industry-year observations per diagnosis category.

Generated Sick Leave Variables. Our outcome variable is the sick leave rate. This variable counts the number of certified sickness spells per 100 enrollees (*sick cases per 100 enrollees*). We transform each dependent variable by taking the logarithm.

Figure 2a shows the distribution of *total sick cases per 100 enrollees* and Figure 2b its logarithm. In both cases we observe relatively symmetric, close to normal, distributions. The untransformed plain variable has a mean of 125, implying 1.25 sick leave cases per year and enrollee across all industries and years. However, the variation ranges from 90 to 163 (Figure 2a and Table A2).

[Insert Figure 2 about here]

Looking at the disease categories and their incidence rates, one finds that the largest disease group is *respiratory diseases*, ICD codes J00-J99, contributing 29% of all cases. Within this group, a third of all cases are due to "bronchitis (J20)", while a quarter is due to "influenza (J09)." Moreover, another fifth is caused by "acute upper respiratory infections (J06)."

The second largest disease group with almost 20% of all cases is *musculoskeletal diseases* (M00-M99), which have the reputation to be particularly prone to shirking behavior. The most noteworthy subcategory in this group is "dorsalgia - back pain (M54)" making up 70% of all musculoskeletal cases.

Next in terms of their incidence relevance are *digestive diseases* (K00-K93, 14%), *injuries and poisoning* (S00-T98, 11%), followed by *infectious diseases* (A00-B99, 6%). The most common digestive disease is "non-infective gastroenteritis (K52, 45%)". Infectious diseases are mainly made up of "viral infections (B34)" and "infectious gastroenteritis (A09)." Together over 80% of all cases coded as infectious diseases fall in these two subcategories.

3.4 Nonparametric Graphical Evidence

Figure 3 shows the "Development of Normalized Sick Leave Cases by Treatment Groups" over time. Figure 3a shows the development for the overall *Sick leave rate*, Figure 3b looks at musculoskeletal diseases, and Figures 3c and d plot diseases of the respiratory system as well as infectious diseases. In addition to being normalized by the number of enrollees, these graphs are also adjusted with respect to the reference year 1994, which is indexed as 100. The two black vertical bars indicate the official implementation dates of the decrease and increase in sick pay generosity, respectively. The representation in Figure 3 serves two main purposes: *(a)* to examine the plausibility of the common time assumption, *(b)* to anticipate and visually illustrate the main findings and help understand how they identify the model in Section 2. Musculoskeletal sick leave cases (aka back pain, Figure 3b) represent the category 'non-infectious diseases' in our model in Section 2, whereas infectious sick leave cases (Figure 3d) represent the category 'infectious diseases' in our model. Respiratory sick leave cases (Figure 3c) is a mixed category.

[Insert Figure 3 about here]

The main identifying assumption in DiD models is the common time trend assumption. It assumes that the outcome variables of all treatment and control groups would have developed in a parallel manner absent the treatment. The standard way to inspect its plausibility is to plot the outcome variables for the different groups graphically and assess their potentially parallel development.

Overall, Figure 3 shows us the following: First, in general the data support the common time trend assumption. Despite some minor spikes here and there, it is obvious that all three groups in the four graphs develop in a pretty parallel manner over the 11 years without reform. In the graphs, this is the case for the time periods before 1997 and after 2000. In particular Figure 3d—showing infectious diseases—illustrates a remarkably parallel development (and does not provide any graphical evidence for a reform effect).

Second, with the exception of infectious diseases, the other three graphs provide strong evidence of a significant reform effect for **Group I** (see Table A1). Immediately after the reform implementation, we observe a 20% decrease in the sick leave rate for the overall disease category.[19] As for musculoskeletal diseases—the category representing non-infectious diseases in our model—the decrease is almost twice as large and around -40% for **Group I**, suggesting strong increases in shirking behavior. As for respiratory diseases—the mixed disease category that also includes flues and common colds—the decrease is only around -10%. Finally, as for infectious disease—the category representing infectious diseases in our model—we do not observe much evidence for any reform effect.

Third, the gap between the differently affected groups unambiguously, not but entirely, closes after 2000. This suggests that the behavioral reaction after the reversal of the sick pay cut kicks in delayed, probably due to the relatively low media coverage when the law was reversed. Moreover,

[19]This is in line with the two other existing studies evaluating this reform using SOEP data (Ziebarth and Karlsson, 2010; Puhani and Sonderhof, 2010)

there is evidence for time persistence or habit formation in sick leave behavior, since the regulations were again identical for all three groups post-1999 (Table A1), and all three groups started with the same initial sick leave level prior to 1997. However, we still observe significant differences between the three groups, even as late as 2004.

Fourth, the reaction to the soft sick pay cut—excluding overtime from the basis of calculation—was obviously asymmetric. Figure 3 does not provide much evidence that excluding overtime affected Group II's behavior in 1997 and 1998. However, the graphical evidence suggests that the very same measure had a significant impact on Group III post 1999.[20]

Relating these findings to our model in Section 2, one can summarize that *(i)* there is clear evidence for a significant and persistent decrease in the absence rate following a sick pay cut, $\beta_t > 0$ (***Proposition 4a***). Similarly, sick leave rates increase when the system becomes more generous. *(ii)* the labor supply adjustment of contagious diseases is smaller (and in fact close to zero) than the adjustment of non-contagious diseases and thus ***Proposition 4c***, $\beta_{nt} > \beta_{ct}$, holds up. In addition, we find a large decrease in shirking $\beta_{nt} > 0$ whereas the increase in presenteeism outweighs additional infections $\beta_{ct} > 0$ (***Proposition 4b***). Finally, because *(iii)* $\beta_{nt} - \beta_{ct} > 0$, the German sick pay cut also led to an increase in infections (***Proposition 4b***).

3.5 Parametric Difference-in-Differences Model

We now estimate the following conventional parametric Difference-in-Differences (DiD) model separately for different disease categories:

$$\begin{aligned} log(y_{it}) = \gamma_i + \beta_0 + &\beta_1 GroupI_i \times' 97 -' 98 + \beta_2 GroupI_i \times' 99 -' 04 + \\ &\beta_3 GroupII_i \times' 97 -' 98 + \beta_4 GroupII_i \times' 99 -' 04 + \\ &+ \delta_t + \mu_{it} \end{aligned} \quad (16)$$

[20]There are two potential explanations for this finding. *(a) Relevance of Relative Changes.* The decrease in sick pay at the end of 1996 was heatedly debated in German society and led to strikes. The main (media) focus was clearly on the decrease in the overall sick pay level. It is plausible that Group II did not react since the main reference point mattered here, which was the decrease in the default federal level. About 50% of all employees experienced a decrease in the level to 80% (Ridinger, 1997; Jahn, 1998). Hence the exclusion of overtime pay was, relatively seen, negligible for affected workers. It may not even have been noticed by the affected employees. After unions managed to negotiate the general sick pay level to remain at 100%, they marketed and emphasized this success accordingly—but either did not mention, or heavily down played the overtime cut. In 1999, by contrast, the exclusion of paid overtime was the only regulatory change that made employees worse off. *(b) LATE.* Since the model identifies the Local Average Treatment Effect (LATE), it could simply be that paid overtime was more relevant for Group III than for Group II.

where $log(y_{it})$ stands for one of our dependent sick leave measures for industry i at time t. γ_i are 17 industry fixed effects and δ_t 10 year fixed effects. The standard errors are routinely clustered at the industry level. We interact the treatment indicators as defined below with two time period dummy variables *'97-'98* and *'99-'04*. The reference period is the years 1994 to 1996.

$GroupI_i$ as well as $GroupII_i$ are binary treatment indicators. As for the 1996 reform, **Group I** experienced a sick pay cut from 100% to 80%, while **Group II** underwent a soft sick pay cut—with paid overtime excluded (Table A1). Group III was not affected, serving as the control group. Thus β_1 identifies the effect of the sick pay cut for **Group I** relative to **Group III** and the years 1997/1998 and relative to the time between 1994 and 1996. Moreover, β_3 identifies the effect of excluding paid overtime for Group II in 1997/1998 relative to the pre-reform period.

As for the 1999 reform, the main pay level was increased again for **Group I**, but overtime excluded from the basis of calculation. **Group II** was not affected and serves as control group.**Group III** experienced a soft cut (Table A1). Thus, β_2 identifies the post-1999 level effect, relative to pre-1997 levels, or the joint effect of the two reforms for **Group I**. Moreover, the difference $\beta_2 - \beta_1$ identifies the effect of the increase in sick pay levels from 80% to 100% after 1999 relative to 1997/1998. In contrast, β_3-β_4 identifies the effect of the overtime exclusion for **Group III** in the post-1999 era relative to pre-1999. Recall that overtime was excluded for Group II in 1997 while nothing happened to Group III, whereas in 1999, overtime was excluded for Group III while nothing happened to Group II. Consequently, $-\beta_4 + \beta_3$ identifies the estimate of the 1999 overtime exclusion for **Group III**. Hence, we differentiate three different groups over three different time periods but only need to estimate four relevant parameters. Since the outcome measures are in logarithms, β_1 to β_4 directly provide the reform-related change of the outcome variable in percent.

3.5.1 Disease-Specific Labor Supply Adjustments: Decomposing Moral Hazard

Estimating $\hat{\beta}_t$, $\hat{\beta}_{nt}$, and $\hat{\beta}_{ct}$. Table 1 shows the results of the DiD model in equation (16) using different outcome variables: the logarithm of *sick cases per 100 enrollees* by the disease categories *total, musculoskeletal, infectious, respiratory,* and *injuries & poisoning*. Each column is one model as in equation (16). For illustrative purposes, we solely show the coefficients of β_1 to β_4 and suppress the remaining ones. In the row below, we *(a)* display the results of an F-test $\beta_2 - \beta_1 = 0$ to test for the effect of the level increase for Group I relative to Group III in 1999. As discussed in Section 3.5, the empirical models closely identify the theoretical model. For example, β_1 in the first row of the first column of Table 1 estimates β_t in equation (14) and tests ***Proposition 4a***. The finding is then crosschecked by $\beta_2 - \beta_1 = 0$ which likewise test ***Proposition 4a*** using the increase in sick pay as as an exogenous source of variation.

Note that the overtime exclusion, or "soft sick pay cut" as we call it, essentially also tests ***Proposition 4a*** and the size and sign of β_t in equation (14) since any variant of making the sick pay less generous could be interpreted as a decrease in sick pay. However, we believe that the best suited coefficient estimates to test ***Propositions 4a-c*** are the ones resulting from $GroupI_i \times' 97 -' 98$—the β_1s for the different disease categories. These are the effects of the initial reduction in the sick pay replacement rate from 100% to 80% in 1997/1998. However, we double and cross-check the consistency and plausibility of these main β_1 findings using the effects of *(i)* the increase in the replacement rate from 80% to 100% in 1999 ($\beta_2 - \beta_1$), the *(ii)* exclusion of overtime for Group II in 1997 (β_3) and Group III and 1999 ($\beta_3 - \beta_4$), as well as *(iii)* the overall development of the sick leave rates from 1999 to 2004—when the system as a whole was more restrictive—relative to 1994 to 1996 (β_2; β_4).

[Insert Table 1 about here]

One can summarize the following from Table 1: First, during the time when sick pay was cut to 80%, in 1997 and 1998, we find overall decreases in the sickness rate by about 22% (β_1 in column (1)). This reflects $\hat{\beta}_t$ in equation (14), i.e., the total moral hazard effect. As seen, β_1 is highly significant and clearly larger than zero, which confirms ***Proposition 4a***. Related to the decrease in sick pay of 20%, one obtains a sickness rate elasticity with respect to the replacement rate of about one. Decreases of about 20% are also found for the 'mixed' infectious and non-infectious category of respiratory diseases (columns (3) and (4)).

Second, musculoskeletal diseases represent the non-contagious disease category n in our model in Section 2. Following the sick pay cut, the sick leave rate of musculoskeletal diseases decreased overproportionally by 34% (column (5), β_1). The overproportional decrease for musculoskeletal diseases, which is composed of 70% back pain cases, fits the common perception that the labor supply of this category is particularly elastic and prone to shirking behavior. Equation (9) of our model illustrates the analytical derivation of β_{nt}. β_{nt}, which is represented by β_1 in column (5) of Table 1, equals the decrease in shirking as sick pay decreases.

Third, infectious diseases, ICD-10 codes A00-B99, represents the contagious disease category c in our model. The estimate stands for the β_{ct} in our model in equation (11). As β_1 in column (2) of Table 1 shows, the infectious disease rate fell underproportionally by an estimated 15% as a response to the sick pay cut in 1997/1998. Note that this estimate is likely upward biased, since the pre-1997 common time trend for infectious diseases is not 100% clean as Figure 3d nicely illustrates. The unbiased estimate likely tends toward zero. In any case, while the findings suggest that $\beta_{nt} > \beta_{ct}$ as formulated in ***Hypothesis 1*** and ***Proposition 4c***, it is also clear that $\hat{\beta}_t > 0$ holds, meaning that the reform led to a decrease in overall sickness absence.

Further Results and Robustness Checks. The labor supply effect in column (6) of Table 1 serves as a robustness test since 50% of all *injuries & poisoning* absences are due to workplace accidents (Bundesverband der Betriebskrankenkassen (BKK), 2004). The first bill that cut sick pay, however, excluded sick leave due to workplace accidents from the cuts (see Table A1). Indeed, as see by β_1 in column (6), the *injuries & poisoning* absence rate decreased underproportionally by almost exactly half the rate than the overall rate, namely by 11.2% instead of 22%.

Second, the β_2 estimate provides the change in sickness rates in the post-1999 era relative to the pre-1997 era for Group I. Meanwhile, the F-test, β_2-$\beta_1 = 0$, yields the effect of the increase in the replacement rate to 100% in 1999. Thus β_2 reflects the long-term impact after a series of reforms that made the overall system more restrictive and shows a decrease of 13.5% at the ten percent significance level for *all diseases*. β_2-β_1 is highly significant for all but infectious diseases. Column (1) suggests that the overall rate increased by 8.4% after the reversal. Column (5) confirms the findings above and suggests that *musculoskeletal diseases*, i.e. back pain, reacted overproportionally with an increase of 19.1% following the increase in sick pay to 100%.

Third, all separate β_3 and β_4 estimates are imprecise and relatively small in size meaning that—in a regression framework that employs industry and year fixed effects—we are unable to detect significant sick leave rate changes in response to the mild sick leave cuts that excluded overtime from the basis of calculation. However, this is at least partly a function of the statistical power that our data offer. Note that all coefficients carry the expected sign and most magnitudes lie around 3 to 5%.

3.5.2 Does the Decrease in Shirking Outweigh the Externalities of Contagious Presenteeism?

Estimating β_{nt}-β_{ct}. To directly test the model predictions, we now pool all disease categories and estimate a triple difference model. ***Proposition 4c*** allows us to directly carry out the following statistical tests $\beta_{nt} = \beta_{ct}$. The triple difference model is similar to the one in equation (16) above but pools all disease groups and adds additional triple interaction terms like $\lambda_1 GroupI_i \times' 97 -' 98 \times Dis_d$, $\lambda_2 GroupI_i \times' 99 -' 04 \times Dis_d$ etc. to the model, where Dis_d represents a vector of disease indicators.

The estimates for λ then directly indicate how the reform effect for every disease category differs from the baseline disease effect.

Table A4 in the Appendix shows the results of this triple difference model. Column (1) of Table A4 simply replicates column (5) of Table 1 focusing on *musculoskeletal diseases*, our proxy for non-contagious diseases.

Column (2) adds the main contagious disease category *infectious diseases* and has thus twice as many observations (396 industry-year estimates). With *musculoskeletal diseases* as the baseline category, the four triple DiD interaction terms *(i)* $GroupI_i \times' 97 -' 98 \times Infectious$, *(ii)* $GroupI_i \times' 99 -' 04 \times Infectious$, *(iii)* $GroupII_i \times' 97 -' 98 \times Infectious$, and *(iv)* $GroupII_i \times' 99 -' 04 \times Infectious$ directly test ***Hypothesis 1*** ($\beta_{nt} = \beta_{ct}$). What Table 1 above already suggested can now be tested with statistical certainty in column (2) of Table A4: $\hat{\beta}_{ct}$-$\hat{\beta}_{nt}$=19.3 percentage points, meaning that the decrease in the contagious sick leave rate was a significant 19.3 percentage points smaller than the decrease in the non-contagious sick leave rate (14.8% vs. 34.1%, see columns (2) and (5) of Table 1). Again, this is likely an underestimate since we likely overestimate β_{ct}. Figures 3b and 3d illustrate very nicely and even more clearly than Table A4 that there was basically no behavioral reaction for *infectious diseases* while one observes substantial behavioral reactions for *musculoskeletal diseases*.

Column (3) additionally adds *respiratory diseases* to the data set. While not all *respiratory diseases* are contagious, this category contains "influenza (J09)", commonly referred to as the flu. As above, the four triple interaction terms identify the differential effect relative to the baseline category *musculoskeletal diseases*. Although we lack statistical power, there is suggestive evidence that the respiratory sick leave rate decreased by about 13% less than the non-contagious baseline. Similarly, the impact of the soft cut for Group III seems to have been less strong.

4 Evidence from US Sick Leave Reforms

This section exploits variation in the implementation of several US sick leave schemes across space and over time in order to test preposition 5. We take advantage of Google Flu Trend data (Google, 2015) at the weekly regional level from 2003 to 2015 to estimate the effect of sick leave on flu rates. Introducing a paid sick leave system is equivalent to increasing sick leave benefit levels which, according to our model, unambiguously increases sick leave utilization ($\frac{\partial \sigma^*(\alpha)}{\partial \alpha} < 0$). Furthermore, access to paid sick leave would lead to an increase in shirking behavior as well as a decrease in contagious presenteeism (Section 2, ***Hypothesis 1***). Unlike in Section 3, we are unable to estimate disease-specific labor supply reactions directly. However, Google Flu Trends allow us to test whether overall population flu infection rates decreased after the legislature mandated employers to provide sick leave opportunities as suggested by ***Proposition 5***. A subsequent decrease in flu infection rates are thus a direct implication of our model and would yield strong evidence for a decrease in contagious workplace presenteeism.

4.1 The US Sick Leave Landscape

The US is the only industrialized country without universal access to paid sick leave. About half of the workforce lacks access to paid sick leave, particularly low-income employees in the service sector (Heymann et al., 2009; Susser and Ziebarth, 2015).

Table B1 in the Appendix provides a comprehensive summary of recent sick pay reform at the city and state level. The details of the bills differ from city to city and state to state but, basically, all sick pay schemes represent employer mandates. Mostly small firms are exempt or face less restrictions. Employees "earn" paid sick pay credit (typically one hour per 40 hours worked) up to nine days per year, and this credit rolls over to the next calendar year if unused. Because employees need to accrue sick pay credit, most sick pay schemes explicitly state a 90 day accrual period. However, the right to take *unpaid* sick leave is part of most sick pay schemes.

As Table B1 shows, San Francisco was the first city to introduce paid sick leave on February 5, 2007. Washington DC followed on November 13, 2008 and extended its sick pay in Feb 22, 2014 to temporary workers and tipped employees. Seattle (September 1, 2012), Portland (Jan 1, 2014), New York City (April 1, 2014), and Philadelphia (May 13, 2015) followed recently. On the state level, we again include the District of Columbia area with the two sick pay introduction and extension in 2008 and 2014 respectively. After that Connecticut (January 1, 2012) followed, however, only applied to service sector employees in non-small businesses and covered about 20% of the workforce. Very recent newly introduced schemes in California (July 1, 2015), Massachusetts (July 1, 2015) and Oregon (Jan 1, 2016) are significantly more comprehensive (see Table B1).

4.2 Exploiting Google Flu Trend Data to Test for Changes in Infections: 2003-2015

We exploit weekly Google Flu Trend data at the city and state level from 2003 to 2015 to test for changes in influenza rates following the introduction of sick pay schemes (Google, 2015). Google provides these data in processed form. The basic idea is that Google search queries can be used to predict and replicate actual influenza infection rates. It has been shown that Google Flu Trends accurately estimates weekly influenza activity in each region of the US (Carneiro and Mylonakis, 2009; Ginsberg et al., 2009).[21]

We use two main Google Flu Trend samples. The first sample contains the weekly flu rates of all major US cities—97 in total—from 2003 to 2015, as listed in columns one and two of Table B2 in the Appendix. The specific start dates are also listed in Table B2.[22] We include data for most cities starting September 28, 2003. The end date for all cities is July 26, 2015. For our first sample of 97 US metropolitan areas, this results in 57,414 city-week observations. The second sample contains all US states and counts 30,141 state-week observations.

Generated Outcome Variable. We use the data that is provided by Google (2015), aggregated at the regional week-of-the-year level. According to Google, strictly speaking, the US data represent the number of influenza-like illnesses (ILI) per 100,000 doctor visits. We take the logarithm of these data as dependent variable.

Hence the dependent variable can be interpreted as "diagnosed influenza-like illnesses (ILI)." Because—unlike in Germany—the US sick pay mandates do not require a doctor's note in order to take sick pay, one would not expect that doctor visits increase due to the sick pay reforms. However, even if that was the case, it still would not be a main threat to our estimates—our estimate of the decrease in influenza-like activity would then represent a lower bound.

Treatment and Control Groups. Table B1 in the Appendix provides the list of cities and states that implemented sick pay schemes between 2006 and 2015. When using our first sample of cities, all seven listed major cities and Washington, DC belong to the treatment group and all other cities to the control group. Analogously, the five states that implemented sick pay schemes so far—District of Columbia, Connecticut, California, Massachusetts, and Oregon—belong to the treatment group in the second sample with state-week observations.

In addition to Google Flu Trend data, we use data from the Bureau of Labor Statistics (BLS, 2015) to control for monthly unemployment rates in our model. The unit of observation in the BLS data is equal to the unit of observation in the Google Flu Trend data. Accordingly, we merge in BLS monthly unemployment rates at the level of the cities and states as reported in Table B2.

[21]There are reports that Google Flu Trends would overestimate actual influenza rates (Lazer et al., 2014). However, even if systematic over- or underestimation occurs, it should not be a threat to our estimates as long as the bias is not correlated with the introduction of sick pay schemes at the regional level. Our rich fixed effects specifications with region and week-of-year fixed effects nets out time-variant seasonal trends in influenza activities and considers time-invariant region specifics. Also note that we used Google Trends retrospectively to test for regional changes in infection rates and do not intend to predict epidemic outbreaks earlier than the Centers for Disease Control and Prevention.

[22]We omit the city of New Orleans which had missings on their variables of interest due to Hurrican Katrina.

4.3 Parametric Difference-in-Differences Model

The staggered implementation of sick pay schemes across space and over time naturally leads to the estimation of the following standard DiD model, similar to the one above for Germany.

$$log(y_{it}) = \phi TreatedCity_i \times LawEffective_t + \delta_t + \gamma_i + Unemp_{it} + \mu_{it} \tag{17}$$

where $log(y_{it})$ is the logarithm of the reported Google (2015) flu rate in city i in week of the year t. γ_i are 96 city fixed effects and δ_t a rich set of week-of-the-year fixed effects over 12 years. $TreatedCity_i$ is a treatment indicator which is one for cities that implemented a sick pay scheme between 2003 and 2015, see Table B1. The interaction with the vector $LawEffective_t$ yields the binary variable of interest. The interaction is one for cities and time periods where a sick pay scheme was legally implemented (see Table B1, column (3)). In addition to the rich set of city and time fixed effects, we control for the monthly BLS provided unemployment rate at the city level, $Unemp_{ci}$. The standard errors are routinely clustered at the city level. Thus this empirical specification allows us to estimate ϕ_t, i.e. the reduction in contagious disease morbidity through the introduction of sick pay defined above.

State Level Estimation. Our second main model specification estimates the entire model at the state-week level. The idea is to capture the effects of the sick pay scheme introduction in the District of Columbia, Connecticut, California, and Massachusetts (see Table B1). Accordingly, we use our second Google Flu Trend sample covering weekly state level data from 2003 to 2015; all i subscripts in equation (17) now represent states, not cities.

Event Study. Lastly, to plot an event study graph, we replace the binary $LawEffective_t$ time indicator with one that continuously counts the number of days until (and from) a law became effective—from -720 days to 0 and +720 days. This allows us to net out, normalize and graphically plot changes in flu rates, relative to when the laws were implemented.

4.3.1 Changes in Influenza Activity When Employees Gain Sick Pay Access

We begin by discussing the estimation results of the DiD model in equation (17). Table 2 shows the findings for our first sample of US cities from 2003 to 2015. As usual, every column represents one model where the first two columns represent the standard model. The only difference between evenly and unevenly numbered columns is that the evenly numbered columns additionally control for the monthly unemployment rate at the city level.

Comparing the *TreatedCity* $\times$ *LawEffective* coefficient estimates in the first two columns, we see that controlling for the monthly unemployment rate barely alters the results — a finding that likewise holds up for columns (3) to (6). Importantly, the first two columns provide negative coefficient estimates that are significant at the 5% level. The literal interpretation would be that influenza-like illnesses (ILI) per 100,000 doctor visits decrease by about 5.5% when employees gain access to paid (and unpaid) sick leave coverage. Pre-reform, roughly half of all employees had no paid sick leave coverage (Susser and Ziebarth, 2015). Although the laws tend to be less stringent for small businesses, as Table B1 shows, most city-based laws are relatively comprehensive and typically cover all private sector employees. Hence, scaling the 5% estimate accordingly implies that population-level influenza infection rates would decrease by about 10% when US employees obtain paid sick leave coverage with the right to take unpaid leave or earn up to nine paid sick days per year.

It is also worthwhile to emphasize that this is a weighted estimate over all seven US cities that implemented paid sick leave, and that these are short- to medium-term estimates. For three cities (NYC, Portland, Newark), we cover more than a year of post-reform influenza activity, and for three other cities (SF, DC, Seattle), we cover at least three years of post-reform influenza rates.

[Insert Table 2 about here]

The models in columns (3) and (4) now replace the city-specific dates indicating when the laws became effective in *LawEffective* (Column (2), Table B1) with the city-specific dates indicating when the laws were *passed* by the city legislature (*LawPassed*). As column (3) of B1 shows, the time span between when the laws were passed and when they became effective amounts up to one year. It is at least imaginable that private firms voluntarily implemented sick pay schemes ahead of the official date. However, as seen, columns (3) and (4) do not provide much evidence that this was the case—the coefficients shrink in size to about 3% and are not statistically significant any more.

Lastly, the models in columns (5) and (6) use time indicators that only become one after the probation or accrual period has been passed (*LawProbation*). As discussed, all laws require employees to "earn" their sick pay. Employees accrue one hour of paid sick leave per 30 or 40 hours of work, i.e., per full-time work week (Table B1). In addition, all laws specify a minimum accrual period of typically 90 days that needs to elapse before employees can take paid sick leave for the first time. Assuming that the first paid sick day can be taken after 12 full work weeks, each earning employees one hour of sick pay, then full-time employees who fall sick are able to take 1.5 paid sick days after 3 months. However, as mentioned, it should be noted that the option to take unpaid sick leave is typically part of these sick pay schemes. Letting the data speak, we can say that the decrease in flu rates increases by one percentage point, when the actual treatment period is defined after the minimum accrual period elapsed. Because the first three months since the implementation of the laws now fall into the pre-reform period which may have already seen decreases in flu activity, we likely underestimate the long-term effect in columns (5) and (6).

Figure 4a shows the Event Study Graph for Table 2. Here we plot the coefficient estimates when we replace the binary time indicators in *LawEffective* with continues time indicators that count the days before and after the laws became effective in each city. Recall that the coefficient estimates are net of city fixed effects and week-of-the-year fixed effects, i.e., correct for common influenza seasonalities across all major US metropolitan areas. Figure 4a demonstrates very little trending in the two years before the sick pay schemes became effective. The coefficient estimates are not statistically different from zero and fluctuate around only slightly around the zero line. In line with the estimate in columns (3) and (4) of Table 2, there is not much evidence for anticipation effects.

Immediately after all employees gained access to paid and unpaid sick leave, the infection rates decrease significantly by up to 20%. Note that the estimates past 480 days following the law lack precision because they are solely based on the experiences in San Francisco (2007), DC (2008 and 2014), and Seattle (2012). New York City's comprehensive bill became effective April 1, 2014—about one year and fours months before the end of our observation period at the end of July 2015. Portland's bill took effect in January 2014 and Newark's bill at the end of May 2014.

Hence, the fact that one seems to observe a long-term rebound of infection rates to the zero line is determined by *(a)* a lack of precision and the early experiences in San Francisco (2007), DC (2008 and 2014), and Seattle (2012). More importantly, the rebound may be driven by *(b)* the confounding effect of the Great Recession in 2009/2010 for San Francisco (it is known that fear of unemployment increases presenteeism) as well as a lax first sick pay law in DC with many exemptions (which was later fixed in 2014). However, overall, Figure 4a nicely illustrates the clear and significant decrease in influenza infection rates at the population level after employees found sick leave coverage. These findings validate our model predictions. They provide strong evidence that contagious presenteeism decreased and that sick and contagious employees stayed at home to recover instead of going to work, and that this change in employee behavior led to the clear decrease in infection rates by up to 20%.

[Insert Figure 4 about here]

The setup of Table 3 follows Table 2. The only difference is that we now estimate the DiD models at the state-week level. States in the treatment group are now the District of Columbia (2008), Connecticut (2012), California (2015), and Massachusetts (2015). However, unfortunately, the bills in California and Massachusetts only became effective July 1, 2015 and our Google Flue Trends observation period ends at the end of July 2015. Hence estimates outside the 26 day post-reform window are exclusively driven by Connecticut and the District of Columbia. In addition, as a reminder, Connecticut's law only covers service sector employees in non-small businesses which represent about 20% of the workforce and also the first DC law was quite lax. Because effectively reducing contagious disease infection rates requires comprehensive measures and preventing infections for as many susceptibles as possible (Vynnycky and White, 2010), and because two important states are only briefly covered in the summer months following the law, we expect the effects of the state level estimates to be less pronounced.

[Insert Table 3 about here]

In line with our expectations, and maybe surprisingly, we still identify a marginally significant decrease in influenza rates of about 2.5% following the laws in the District of Columbia, Connecticut, California, and Massachusetts (Columns (1) and (2)). Again, there is not much evidence that a significant amount of employers (who did not provide paid sick leave to this date) provided sick pay voluntarily between the passage of the law and its implementation. The size of the coefficients in columns (3) and (4) are attenuated, only around -1%, but not statistically significant. The same is true for the estimates in columns (5) and (6) which are solely based on the District of Columbia and Connecticut because the end of the official accrual period (90 days) lies outside of our window of observation for California and Massachusetts.

The event study in Figure 4b provides a clearer picture. While the two year period before the reform implementation provides estimates that fluctuate consistently around the zero line and are never significantly different from zero, the infection rates slightly trend downward in the post-reform period. However, the estimates are partly noisy and lack statistical power. Again, recall that only the first 26 days are based on evidence from four states, while all other post-reform estimates are exclusively based on the patchy Connecticut bill and the two step introduction in the District of Columbia.

5 Conclusion

Empirically identifying presenteeism behavior is extremely challenging, yet crucial in order to test for one major economic justification for publicly provided sick pay: the negative externalities associated with contagious presenteeism. Contagious presenteeism refers to the phenomenon when employees with infectious diseases go to work sick and infect co-workers and customers. Such behavior is a major public health issue and one driving force of the spread of contagious diseases. If contagion is unobservable, which is usually the case at the beginning of a sickness episode, then state regulation may reduce market inefficiencies by mandating employers to provide monetary incentives for employees to stay home when sick. If such monetary incentives work, and economic theory as well empirical studies strongly suggest that they do, then public sick pay schemes reduce contagious presenteeism and the spread of diseases.

To our knowledge, this study is the first that theoretically derives and empirically implements tests for the existence of contagious presenteeism and negative externalities in sickness insurance schemes. First, our model theoretically defines different possible cases of workplace absence behavior under contagious and non-contagious continuous sickness levels. As such, we also decompose classical moral hazard into *(i)* shirking behavior, and *(ii)* contagious presenteeism. Case *(i)* does not imply negative health spillovers, whereas case *(ii)* does. We derive conditions to be able to test for moral hazard and its decomposed elements *(i)* and *(ii)*.

We first exploit two German sick pay reforms and administrative physician-certified sick leave data at the industry-level to provide empirical evidence for the existence of contagious presenteeism, which we indeed find. However, we also show that, in Germany, with one of the most generous sick leave systems worldwide, the reduction in shirking behavior was larger than the increase in the infectious disease rate (due to contagious presenteeism) when sick pay was cut from a baseline level of 100%.

Next, we exploit the staggered implementation of employer sick pay mandates at the city and state level in the US. Using Google Flu Trends data, we show that influenza rates decrease significantly when employees gain access to paid sick leave. About half of all US employees do not have access to paid sick leave. The relatively comprehensive laws at the level of seven major US cities and our estimates suggest that influenza-like infection rates decrease by about 10% when employees without coverage obtain access to paid or unpaid sick leave. Although most city ordinances are comprehensive in the sense that they cover all employees and provide a wage replacement of 100%, they are less comprehensive in the sense that employees have to work one week full-time to earn one hour of sick leave up to a maximum of typically eight days per year. Hence, a significant share of the reduction in infection rates found in this paper is likely driven by legally guaranteed access to *unpaid* leave. The findings suggest that infections rates may further decrease in the medium to long-run when employees have accrued a significant amount of paid sick days.

Researchers should exploit different settings and our proposed method, or variants of it, to test for the existence and the degree of contagious presenteeism, shirking behavior, and the overall level of moral hazard. Important fields of applications include *(a)* contagious presenteeism by teachers or school kids, e.g., induced by teacher or parental sick pay schemes that may or may not cover sickness of children. Schools are important sources for the spread of contagious diseases. Another relevant setting would be the firm level to test for *(b)* contagious presenteeism behavior by employees with a high degree of customer contact and related decreases in productivity. As a last example, *(c)* contagious presenteeism behavior by health care workers can be life-threatening for patients, but potentially be minimized by optimized sick pay schemes. Note that our test can be carried out using many different types of data, including school-level, firm-level data, or hospital-level data. Ideally, one would want to exogenously vary the generosity of the sick pay scheme under investigation, then measure changes in shirking and contagious presenteeism behavior, and then re-adjust until both undesirable employee behaviors are minimized.

More research is also needed in order to better understand how exactly contagious presenteeism leads to infections of co-workers and customers and how it affects overall workplace productivity. Firm-level and employee-level compensation strategies to dampen sickness-related productivity losses are also fruitful relevant research questions.

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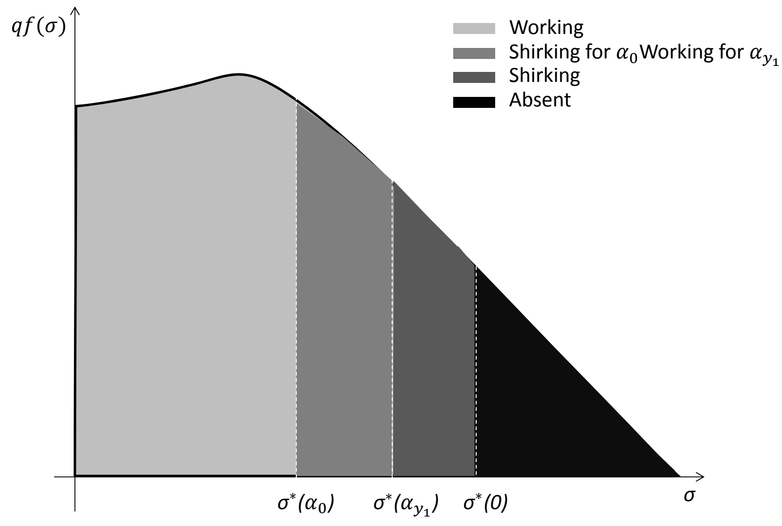
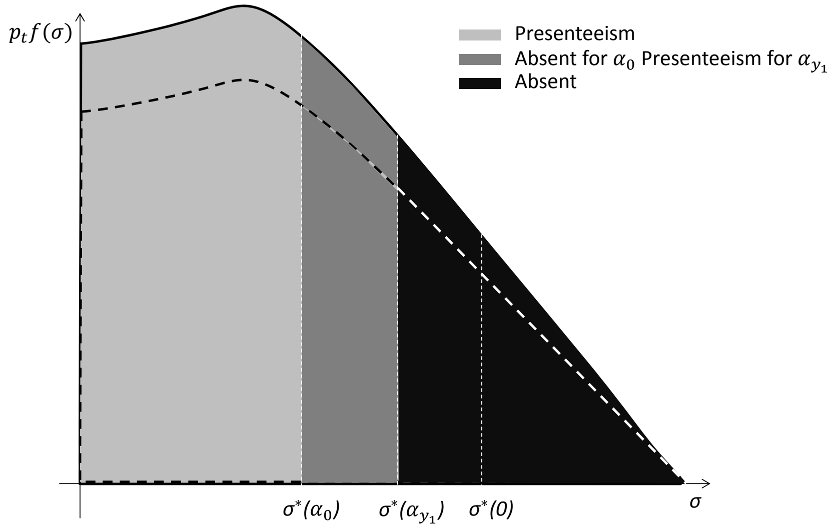
Figures and Tables

Figure 1: Graphical Representation and Classification of Shares of Employees Working and on Sick Leave

Panel A: Non-Contagious Diseases



Panel B: Contagious Diseases



Panel A shows the share of employees who draw a non-contagious disease. After the sick pay cut, shirking decreases. Panel B depicts the same situation for contagious diseases. A sick pay cut increases contagious presenteeism and p_t, represented by the outward shift of the curve.

Figure 2: Distribution of (a) Sick Leave Cases and (b) Logarithm of Sick Leave Cases per 100 Employees

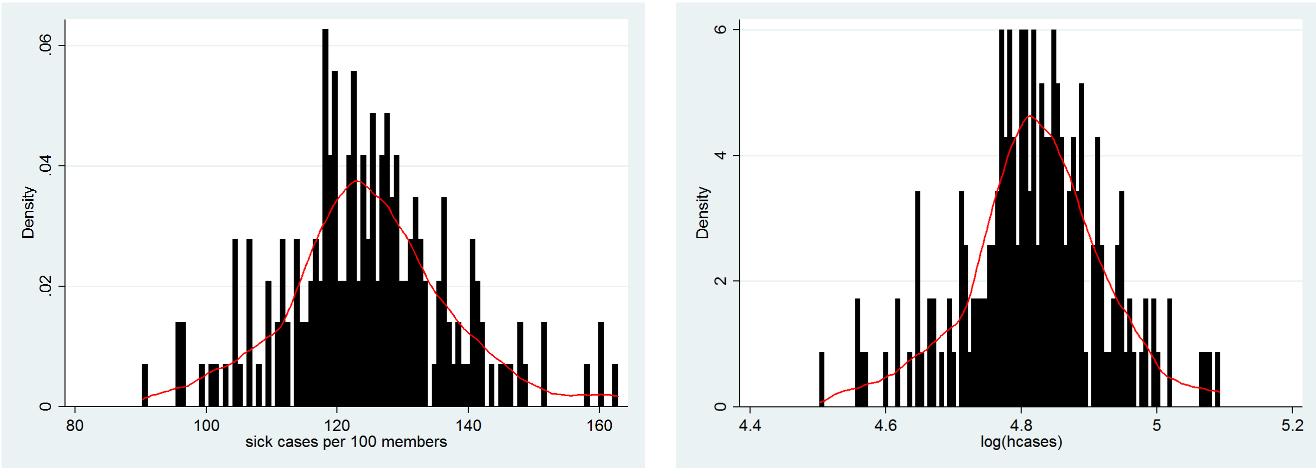
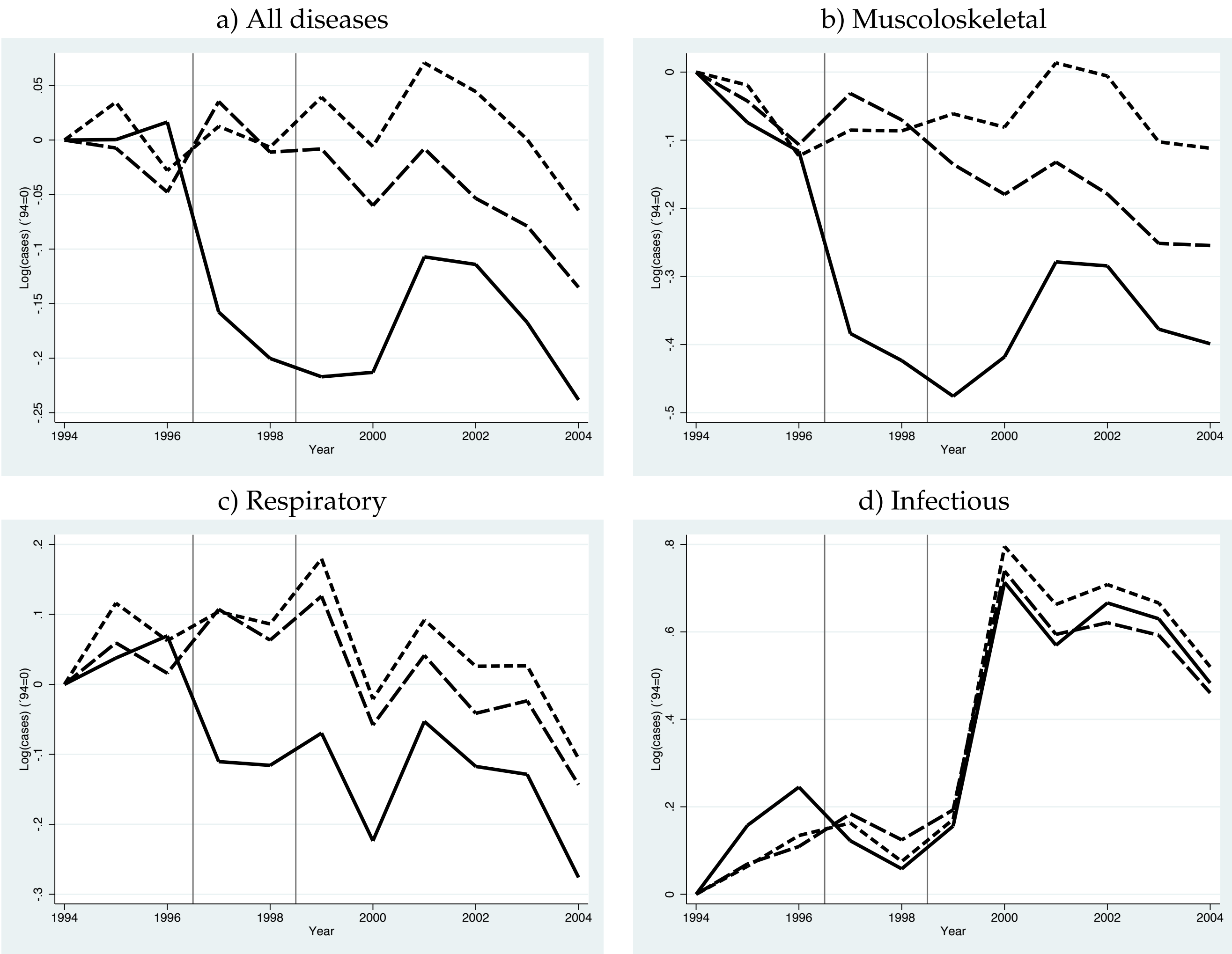


Figure 3: Development of Sick Leave Rates by Treatment Groups Over Time



The solid line shows the development of industries in **Group I**. This group experienced a sick pay cut from 100% to 80% in 1997 and the reverse of this cut in 1999. The short dashed line represents **Group II**. This group witnessed a "soft cut" in 1997 through the exclusion of overtime. Finally, the long dashed line depicts **Group III**, which had a soft cut in 1999. For more information about the sick pay reforms, see Table A1.

Figure 4: Event Study—Effect of Sick Pay Mandates on

Panel A: Cities

Panel B: States

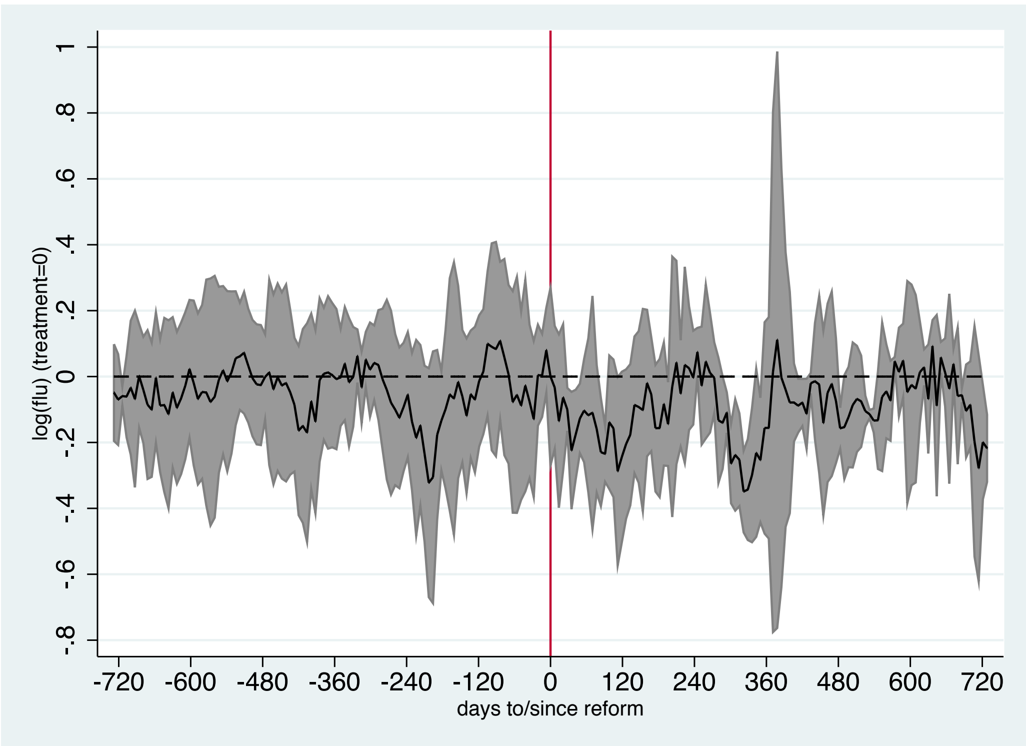


Table 1: Effect of Changes in Sick Pay on Normalized Cases of Sick Leave by Disease Groups

	All diseases (1)	Infectious (2)	Respiratory (3)	Musculosk. (5)	Inj. & Pois. (6)
Group I×'97-'98	-0.220***	-0.148***	-0.208***	-0.341***	-0.112**
(Effect of Cut '97)	(0.057)	(0.047)	(0.054)	(0.076)	(0.045)
Group I×'99-'04	-0.135*	-0.075	-0.131***	-0.150	0.030
(Level post-'99 vs. pre-'97)	(0.070)	(0.053)	(0.044)	(0.157)	(0.087)
Group II×'97-'98	-0.029	-0.041	-0.022	-0.038	-0.006
(Effect of Soft Cut '97)	(0.065)	(0.073)	(0.061)	(0.086)	(0.065)
Group II×'99-'04	0.053	0.053	0.017	0.131	0.107
(Level post-'99 vs. pre-'97)	(0.078)	(0.070)	(0.055)	(0.164)	(0.095)
[Group I×'99-'04] - [Group I×'97-'98]	0.084***	0.073	0.077***	0.191**	0.142***
pvalue	0.000	0.121	0.000	0.032	0.004
(Effect of Increase '99)					
R2	0.659	0.949	0.816	0.858	0.918
Observations	198	198	198	198	198
Number of industries	18	18	18	18	18

Source: (Bundesverband der Betriebskrankenkassen (BKK), 2004), own calculation and illustration; * $p<0.1$, ** $p<0.05$, *** $p<0.01$; standard errors in parentheses are clustered at the industry-level. All regressions are weighted by the annual number of industry-specific sickness fund enrollees. The descriptive statistics are in the Appendix (Table A2). Each column represents one model as in equation (16), estimated by OLS, i.e., all models include industry and year fixed effects. The dependent variables are logarithms of the normalized sick leave cases per 100 employees. Column (1) employs the total number of sick leave cases as dependent variable, column (2) solely uses certified infectious sick leave cases and so on. For more information on how the variables were generated, see Section 3.3. *Treated* is a treatment indicator with one for **Group I** and zero for **Group III**, whereas *PartlyTreated* is one for **Group II** and zero for **Group III**. **Group I** experienced a sick pay cut from 100 to 80% in 1997 and a reversal in 1999. **Group II** experienced a soft cut in 1997 and **Group III** experienced a soft cut in 1999. For more information about the sick pay reforms, see Table A1.

Table 2: Effect of Introduction of Sick Pay Mandates on Influenza Rate (Sample I: US Cities 2003-2015)

	(1) Flu	(2) Flu	(3) Flu	(4) Flu	(5) Flu	(6) Flu
TreatedCity×LawEffective	-0.0572**	-0.0554**				
	(0.0234)	(0.0230)				
TreatedCity×LawPassed			-0.0300	-0.0281		
			(0.0233)	(0.0235)		
TreatedCity×ProbationOver					-0.0643**	-0.0628**
					(0.0291)	(0.0285)
N	57,414	57,414	57,414	57,414	57,414	57,414

Source: (Google, 2015), own calculation and illustration; * p<0.1, ** p<0.05, *** p<0.01; standard errors in parentheses are clustered at the city level. The dependent variable is always the logarithm of the number of influenza-like illnesses (ILI) per 100,000 doctor visits as reported by Google (2015). All regressions contain week-of-year fixed effects and city fixed effects as in equation (17). Each column represents one model, estimated by OLS. Even numbered columns additionally control for the local monthly unemployment rate (BLS, 2015). *TreatedCity* is a treatment indicator which is one for all cities listed in Table B1. The entire sample of cities considered is in columns one and two of Table B2.

Table 3: Effect of Introduction of Sick Pay Mandates on Influenza Rate (Sample II: US States 2003-2015)

	(1) Flu	(2) Flu	(3) Flu	(4) Flu	(5) Flu	(6) Flu
TreatedState×LawEffective	-0.0223*	-0.0264*				
	(0.0131)	(0.0147)				
TreatedState×LawPassed			-0.00889	-0.0113		
			(0.0179)	(0.0198)		
TreatedState×ProbationOver					-0.0139	-0.0185
					(0.0104)	(0.0112)
N	30141	30141	30141	30141	30141	30141

Source: (Google, 2015), own calculation and illustration; * p<0.1, ** p<0.05, *** p<0.01; standard errors in parentheses are clustered at the state level. The dependent variable is always the logarithm of the number of influenza-like illnesses (ILI) per 100,000 doctor visits as reported by Google (2015). All regressions contain week-of-year fixed effects and state fixed effects as in equation (17). Each column represents one model, estimated by OLS. Even numbered columns additionally control for the monthly unemployment rate in the state (BLS, 2015). *TreatedState* is a treatment indicator which is one for all states listed in Table B1. The entire sample of states considered is in column three of Table B2.

Appendix A

Table A1: Detailed Overview of Reductions and Increases in German Federal Employer Sick Pay Mandates and Industry-Specific Collective Agreements

	Before 10/1996 **(1)**	**10/1996-12/1998** **(2)**	**Since 1/1999** **(3)**
Panel A: Federal Employer Mandate Regulations			
	100% sick pay No waiting period for new employees Paid overtime included in basis of calculation Extra payments included in basis of calculation	**80% sick pay** **Waiting period 4 weeks** Paid overtime included in basis of calculation **Extra payments can be contractually excluded** **No cut if 1 day of paid vacation traded for 5 sick days**	**100% sick pay** Waiting period 4 weeks **Paid overtime excluded in basis of calculation** Extra payments can be contractually excluded
Panel B: Industry-Specific Collective Bargaining Regulations			
Group I		80% sick pay during first 3 days (eff. July 1, 1997)	
Group II		100% sick pay Paid overtime excluded in basis of calculation	
Group III		100% sick pay	
Panel C: Combined Effect for Different Industries			
Group I	as in Panel A	**80% sick pay, since 07/'97 during first 3 days** **Waiting period 4 weeks**	**100% sick pay** Waiting period 4 weeks **Paid overtime excluded in basis of calculation**
Group II	as in Panel A	100% sick pay **Waiting period 4 weeks** **Paid overtime excluded in basis of calculation**	100% sick pay Waiting period 4 weeks Paid overtime excluded in basis of calculation
Group III	as in Panel A	100% sick pay **Waiting period 4 weeks**	100% sick pay Waiting period 4 weeks **Paid overtime excluded in basis of calculation**

Source: (Hans Böckler Stiftung, 2014), own illustration. *Group I* is composed of the construction sector. *Group II* contains the following industries: steel, textile, mechanical engineering, automobile, ship and aerospace, electrical engineering and optics, wood and paper, printing, food and hospitality, trade, banking and insurance. *Group III* represents the chemical, oil, glass, energy and water, postal and transportation as well as public administration sector. Changes in regulation between time periods are in bold. The negotiated agreements cover 1.1M employees in *Group I* and at least 4.5M in *Group II* and 4M in *Group III* (Jahn, 1998; Hans Böckler Stiftung, 2014).

Table A2: Descriptive Statistics of Sick Leave Measures

Variable	Mean	Std. Dev.	Min.	Max.	N
Total sick cases per 100 enrollees	122.3	11.5	90.3	162.8	198
Total log(cases)	4.80	0.1	4.50	5.09	198
Infectious sick cases per 100 enrollees	8.2	2.2	3.9	14.9	198
Infectious log(cases)	2.07	0.29	1.36	2.70	198
Respiratory sick cases per 100 enrollees	35.4	4.3	25.2	50.0	198
Respiratory log(cases)	3.56	0.12	3.23	3.91	198
Digestive sick cases per 100 enrollees	16.3	2.0	12.8	24.0	198
Digestive log(cases)	2.79	0.12	2.55	3.18	198
Musculoskeletal sick cases per 100 enrollees	22.7	4.9	9.8	34.4	198
Musculoskeletal log(cases)	3.10	0.24	2.28	3.54	198
Injury sick cases per 100 enrollees	12.7	3.2	6.8	23.5	198
Injury log(cases)	2.51	0.25	1.92	3.16	198

Sources: (Bundesverband der Betriebskrankenkassen (BKK), 2004), own calculation and illustration. Descriptives are weighted by the annual number of industry-specific sickness fund enrollees.

Table A3: **Number of Enrollees per Industry and Treatment Group**

Industry and Classification	**Mean**	**Std. Dev.**
Group I		
Construction	127,642	104,205
Group II		
Steel	109,397	7,405
Textile	32,367	7,854
Mechanical Engineering	191,391	44,035
Automobile	301,725	43,313
Ship and Aerospace	33,626	9,323
Electrical engineering, optics	306,296	71,383
Wood and Paper	57,070	27,307
Printing	38,477	19,605
Food and Hospitality	55,045	33,748
Trade	341,566	227,279
Banking and Insurance	149,188	74,095
Group III		
Chemical	230,382	46,215
Oil	15,586	5,074
Glass	34,097	5,480
Energy and Water	50,702	13,149
Postal and Transportation	478,490	104,031
Public Administration	732,958	476,804

Sources: (Bundesverband der Betriebskrankenkassen (BKK), 2004), own calculation and illustration.

Table A4: Effect of Changes in Sick Pay on Normalized Cases of Sick Leave—Pooled Regressions

	(1) Musculoskeletal	(2) Musculoskeletal, Infectious	(3) Muscul., Infect. Respiratory
Group I×'97-'98	-0.341***	-0.341***	-0.341***
	(0.076)	(0.075)	(0.075)
Group I×'99-'04	-0.150	-0.150	-0.150
	(0.157)	(0.155)	(0.154)
Group II×'97-'98	-0.038	-0.038	-0.038
	(0.086)	(0.085)	(0.085)
Group II×'99-'04	0.131	0.131	0.131
	(0.164)	(0.161)	(0.161)
Group I×'97-'98×Infectious		0.193**	0.193**
		(0.088)	(0.088)
Group I×'99-'04×Infectious		0.075	0.075
		(0.164)	(0.163)
Group II×'97-'98×Infectious		-0.003	-0.003
		(0.112)	(0.111)
Group II×'99-'04×Infectious		-0.079	-0.079
		(0.176)	(0.175)
Group I×'97-'98×Respiratory			0.133
			(0.092)
Group I×'99-'04×Respiratory			0.019
			(0.160)
Group II×'97-'98×Respiratory			0.016
			(0.104)
Group II×'99-'04×Respiratory			-0.115
			(0.170)
Observations	198	396	594
R2	0.858	0.982	0.989

Source: (Bundesverband der Betriebskrankenkassen (BKK), 2004), own calculation and illustration; * $p<0.1$, ** $p<0.05$, *** $p<0.01$; standard errors in parentheses are clustered at the industry-disease-level. All regressions are weighted by the annual number of industry-specific sickness fund enrollees. The descriptive statistics are in the Appendix (Table A2). The regressions are based on equation 17. The model in the first column equals the fifth column of Table 1. The model in the second column pools the two categories musculoskeletal and infectious, where musculoskeletal form the reference group. The third column additionally adds respiratory diseases. The fourth column adds all other diseases as a separate category. All regressions are estimated by OLS and include industry, disease and year fixed effects. The dependent variables are logarithms of the normalized sick leave cases per 100 employees. For more information on how the variables were generated, see Section 3.3. *Treated* is a treatment indicator with one for **Group I** and zero for **Group III**, whereas *PartlyTreated* is one for **Group II** and zero for **Group III**. **Group I** experienced a sick pay cut from 100 to 80% in 1997 and a reversal in 1999. **Group II** experienced a soft cut in 1997 and **Group III** experienced a soft cut in 1999. For more information about the sick pay reforms, see Table A1.

Appendix B

Table B1: Overview of Employer Sick Pay Mandates in the US

Region (1)	Law Passed (2)	Law Effective (3)	Content (4)
San Francisco, CA	Nov 7, 2006	Feb 5, 2007	all employees including part-time and temporary; 1 hour of paid sick leave for every 30 hours worked; up to 5 to 9 days depending on firm size; for own sickness or family member; 90 days accrual period
Washington, DC	May 13, 2008	Nov 13, 2008	'qualified employees'; 1 hour of paid sick leave for every 43 hours, 90 days accrual period; up to 3 to 9 days depend. on firm size; own sickness or family; no health care or restaurant workers
	Dec 18, 2013 (extension pending funding)	Feb 22, 2014 (retrospective in Sep 2014)	extension to 20,000 temporary workers and tipped employees
Connecticut	July 1, 2011	Jan 1, 2012	full-time service sector employees in firms>49 employees (20% of workforce); 1 hour for every 40 hours; up to 5 days; own sickness or family member, 680 hours accrual period (4 months)
Seattle, WA	Sep 12, 2011	Sep 1, 2012	all employees in firms with >4 full-time employees; 1 hour for every 30 or 40 hours worked; up to 5 to 13 days depending on firm size, for own sickness or family member; 180 days accrual period
New York, NY	June 26, 2013 Jan 17, 2014 extended	April 1, 2014 (pending economy)	employees w >80 hours p.a in firms >4 employees or 1 domestic worker; 1 hour for every 30 hours; up to 40 hours; own sickness or family member; 120 days accrual period
Portland, OR	March 13, 2013	Jan 1 2014	employees w >250 hours p.a. in firms >5 employees; 1 hour for every 30 hours; up to 40 hours; own sickness or family member
Newark, NJ	Jan 29, 2014	May 29, 2014	all employees in private companies; 1 hour of for every 30 hours; 90 days accrual period; up to 24 to 40 hours depending on size; own sickness or family
Philadelphia, PA	Feb 12, 2015	May 13, 2015	employees in firms >9 employees; 1 hour of paid sick leave for every 40 hours; 90 days accrual period; up to 40 hours; own sickness or family member
California	September 19, 2014	July 1, 2015	all employees; 1 hour of paid sick leave for every 30 hours; 90 days accrual period; minimum 24 hours; own sickness or family member
Massachusetts	Nov 4, 2014	July 1, 2015	employees in firms >10 employees; 1 hour of paid sick leave for every 40 hours; 90 days accrual period; up to 40 hours; own sickness or family member
Oakland, CA	Nov 4, 2014	March 2, 2015	employees in firms >9 employees; 1 hour of paid sick leave for every 30 hours; 90 days accrual period; up to 40 to 72 hours depending on firm size; own sickness or family member
Oregon	June 22, 2015	Jan 1, 2016	employees in firms >9 employees; 1 hour of paid sick leave for every 30 hours; 90 days accrual period; up to 40 hours; own sickness or family member

Source: several sources, own collection, own illustration.

Table B2: US Cities and States (in alphabetical order) with Weekly Google Flu Data As Of

City	Month	Day	Year	City	Month	Day	Year	State	Month	Day	Year
Albany, NY	9	28	2003	Mesa, AZ	11	7	2004	Alabama	28	9	2003
Albuquerque, NM	10	12	2003	Miami, FL	9	28	2003	Alaska	12	12	2004
Anchorage, AK	10	17	2004	Milwaukee, WI	9	28	2003	Arizona	28	9	2003
Arlington, VA	9	28	2003	Nashville, TN	9	28	2003	Arkansas	7	11	2004
Atlanta, GA	9	28	2003	New York, NY	9	28	2003	California	28	9	2003
Austin, TX	9	28	2003	Newark, NJ	9	28	2003	Colorado	28	9	2003
Baltimore, MD	9	28	2003	Norfolk, VA	9	28	2003	Connecticut	28	9	2003
Baton Rouge, LA	9	26	2004	Oakland, CA	9	28	2003	Delaware	30	10	2005
Beaverton, OR	12	14	2003	Oklahoma City, OK	9	28	2003	District of Columbia	28	9	2003
Bellevue, WA	11	30	2003	Omaha, NE	9	28	2003	Florida	28	9	2003
Berkeley, CA	9	19	2004	Orlando, FL	9	28	2003	Georgia	28	9	2003
Birmingham, AL	9	28	2003	Philadelphia, PA	9	28	2003	Hawaii	2	11	2003
Boise, ID	10	3	2004	Phoenix, AZ	9	28	2003	Idaho	14	11	2004
Boston, MA	9	28	2003	Pittsburgh, PA	9	28	2003	Illinois	28	9	2003
Buffalo, NY	10	19	2003	Plano, TX	10	16	2005	Indiana	28	9	2003
Cary, NC	9	26	2004	Portland, OR	9	28	2003	Iowa	28	9	2003
Charlotte, NC	9	28	2003	Providence, RI	10	17	2004	Kansas	28	9	2003
Chicago, IL	9	28	2003	Raleigh, NC	9	28	2003	Kentucky	28	9	2003
Cleveland, OH	9	28	2003	Reno, NV	10	24	2004	Louisiana	28	9	2003
Colorado Springs, CO	9	19	2004	Reston, VA	11	28	2004	Maine	31	10	2004
Columbia, SC	10	10	2004	Richmond, VA	9	28	2003	Maryland	28	9	2003
Columbus, OH	9	28	2003	Rochester, NY	9	28	2003	Massachusetts	28	9	2003
Dallas, TX	9	28	2003	Roswell, GA	11	23	2003	Michigan	28	9	2003
Dayton, OH	11	23	2003	Sacramento, CA	9	28	2003	Minnesota	28	9	2003
Denver, CO	9	28	2003	Salt Lake City, UT	9	28	2003	Mississippi	28	11	2004
Des Moines, IA	10	17	2004	San Antonio, TX	9	28	2003	Missouri	28	9	2003
Durham, NC	9	28	2003	San Diego, CA	9	28	2003	Montana	27	11	2005
Eugene, OR	10	17	2004	San Francisco, CA	9	28	2003	Nebraska	9	11	2003
Fresno, CA	12	7	2003	San Jose, CA	9	28	2003	Nevada	23	11	2003
Ft Worth, TX	10	3	2004	Santa Clara, CA	9	28	2003	New Hampshire	30	11	2003
Gainesville, FL	10	12	2003	Scottsdale, AZ	10	24	2004	New Jersey	28	9	2003
Grand Rapids, MI	10	3	2004	Seattle, WA	9	28	2003	New Mexico	17	10	2004
Greensboro, NC	11	14	2004	Somerville, MA	9	28	2003	New York	28	9	2003
Greenville, SC	10	24	2004	Spokane, WA	1	16	2005	North Carolina	28	9	2003
Honolulu, HI	9	28	2003	Springfield, MO	10	30	2005	North Dakota	12	11	2006
Houston, TX	9	28	2003	St Louis, MO	9	28	2003	Ohio	28	9	2003
Indianapolis, IN	9	28	2003	St Paul, MN	9	28	2003	Oklahoma	28	9	2003
Irvine, CA	10	3	2004	State College, PA	9	5	2004	Oregon	28	9	2003
Irving, TX	9	28	2003	Sunnyvale, CA	9	28	2003	Pennsylvania	28	9	2003
Jackson, MS	11	14	2004	Tampa, FL	9	28	2003	Rhode Island	24	10	2004
Jacksonville, FL	10	3	2004	Tempe, AZ	9	28	2003	South Carolina	28	9	2003
Kansas City, MO	9	28	2003	Tucson, AZ	9	28	2003	South Dakota	5	11	2006
Knoxville, TN	10	3	2004	Tulsa, OK	9	28	2003	Tennessee	28	9	2003
Las Vegas, NV	9	28	2003	Washington, DC	9	28	2003	Texas	28	9	2003
Lexington, KY	9	26	2004	Wichita, KS	9	26	2004	Utah	9	11	2003
Lincoln, NE	10	31	2004					Vermont	30	10	2005
Little Rock, AR	10	3	2004					Virginia	28	9	2003
Los Angeles, CA	9	28	2003					Washington	28	9	2003
Lubbock, TX	10	17	2004					West Virginia	21	11	2004
Madison, WI	9	28	2003					Wisconsin	28	9	2003
Memphis, TN	10	24	2004					Wyoming	2	12	2007

Source: Google (2015), own collection, own illustration. The table indicates the first observation period and all cities (Sample I) and states (Sample II) included. The last observation period is July 26, 2015 for the whole sample.