Employment Protection and Child Development

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December 2022

Abstract

This paper exploits conditional random assignment of patients to general practitioners to calculate a leniency measure of paid sick leave certification. We link these data to information on the human capital development of the patients' children. We find sizable negative effects of parental sick leave enrollment on the child's human capital development. In addition, we show that the timing of parental enrollment in these programs matter. In terms of mechanisms, we find that sick leave makes parents more likely to exit the workforce, earn lower wages, and become increasingly dependent on the social safety net. The results highlight that the trade-off between social protection and work incentives extends well beyond the individual worker, and emphasizes another dimension of the home environment through which children's human capital is shaped. In addition, it implies that the costs of traditional employment protection programs are larger than previously thought.

JEL Codes: I10, I20, J20, J60
Keywords: Human Capital Development, Skill Formation, Employment Protection, Intergenerational Links, Welfare Dependence, Sick Leave

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1 Introduction

Children are highly affected by their home environments, and there exists a rich literature examining how the structure and resources of families influence the human capital development of children (e.g., Knudsen et al. (2006); Cunha et al. (2006); Heckman and Mosso (2014)). Employment protection and social security programs that shield children from abrupt changes to the home environment may therefore play an important role in their development. However, the effects of traditional employment protection policies on child development are theoretically ambiguous and empirically unknown.

In theory, conventional employment protection policies such as paid sick leave and unemployment benefits may help child development. Not only does it limit the financial impact of adverse household-level shocks, but it also reduces the stress and mental health burden associated with such events. This may provide the parent with a smoother transition back into the labor force after the shock and ensure stress-free and high-quality child-parent interactions during the shock. However, these programs may also hurt child development. This would be the case if program participation generates increased welfare dependence, negatively impacts the parent's long-run labor market trajectory, and transmits negative role model/perception signals to the child. In addition, the effect on child development may depend on when program enrollment occurs during the child's upbringing. Specifically, the life-cycle approach to skill formation suggests that children's development depends not only on how much investment occurs during their childhood, but also on its timing (e.g., Heckman (2007)). As such, exposure at key stages of development may be fundamentally different from exposure at other ages.

The theoretical ambiguity surrounding the impact of employment protection on child development necessitates an empirical analysis on the topic. Such analyses are difficult to perform, not only because it requires very detailed multi-generational data that spans many years, but also because it requires variation in parental employment protection take-up that is uncorrelated with other determinants of child development. In this paper, we overcome these challenges and examine both the direct impact on children as well as the channels through which the effects operate. In addition, we explore the timing of the effects across childhood, and whether the effects vary as a function of how close the parental program take-up is to sensitive learning periods during the child's upbringing.

To perform our analysis, we exploit key institutional features of the Norwegian sick leave system in combination with extremely rich administrative data. Specifically, we leverage conditional random assignment of patients to general practitioners (GPs) to calculate a leniency measure of paid sick leave certification. We then link this data with the human capital development of the parents' children across their childhood. Two specific features of the Norwegian system make this an ideal setting for our analysis. First, any absence from work longer than three days requires a GP approval, and assignment to a more or less lenient GP can therefore make the difference between being granted paid sick leave or not.[1] Second, when GPs retire or move – or for some other reason outside the patient's control become unavailable – the Norwegian Health Economics Administration randomly reassigns patients to new local GPs conditional on municipality and availability. We can therefore use GP reassignments due to causes outside the patient's control as a source of exogenous variation in doctor-patient assignment to identify sick leave certification leniency of physicians. In all our specifications, we include previous GP fixed effects, such that we compare individuals who originally had the same GP, but that were reallocated to new – and different – GPs because of external factors outside their control.

After having estimated the leniency of GPs in Norway and explored the impact on child development, we investigate potential mechanisms that may explain the effects we observe. We do this by linking the patient data to a rich set of labor market and welfare participation information, enabling us to determine the impact of sick leave on the parents themselves – and through which of these channels the effect on children may operate.

[1] In the public sector, the rules are slightly more generous, with employees being allowed to self-report 1.5 weeks of sickness absence prior to requiring the GPs approval. However, the effects are relatively similar across the public and the private sector (see Section 5 for results and discussion).

In terms of identification assumptions, our leniency measure is identified under the assumption that the exogenous GP reassignments – conditional on previous GP fixed effects – are uncorrelated with other factors of the patients that may also affect their children's human capital development. In theory, the validity of this assumption follows directly from the fact that the Norwegian Health Economics Administration randomly reassigns patients to new local GPs when their old GPs no longer are available. In practice, it is possible to obtain suggestive evidence on the validity of this assumption by examining if leniency of the exogenously-assigned GP is uncorrelated with observed patient characteristics. Using a rich set of patient characteristics, we provide strong evidence in support of this assumption.

Our analysis generates five core results. First, we show that there is considerable variation in sick leave probability as a function of the leniency of the GP that the patient is assigned. Specifically, assignment to a one standard deviation more lenient GP generates approximately 2 additional weeks of sick leave in the following year. Variation in leniency is much more pronounced for hard-to-verify musculoskeletal and psychological causes for which GPs have more individual freedom to choose whether to grant sick leave or not. In addition, we find no relationship between a GP's sick leave leniency measure and measures of GP quality such as mortality, value-added, number of patients, check-up rate, inpatient visits, or ER visits. This points to the subjectivity involved in the sick leave certification process, and demonstrates that this subjectivity is not correlated with other characteristics of GPs (in particular their ability to improve the health of patients) that could contribute to the results on the human capital development of the assigned parents' children that we find.

Second, we find economically sizable and statistically significant negative effects of parental sick leave enrollment across the child's human capital development. Specifically, a one standard deviation increase in the leniency of a parent's GP is associated with a decline in compulsory school GPA by 3 percent of a standard deviation and a decline in high school GPA of approximately the same size. This is an economically meaningful decline, though smaller than estimated effects of more conventional direct education inventions such as class size reductions, teacher quality improvements, or resource increases.

Third, we find that the effects on the children's human capital development are not only operating on the intensive margin of education attainment, but are also present on the extensive margin. Specifically, in response to the parent being assigned a GP who is 1 SD more lenient, we find a reduction in the probability of graduating high school by 1.2 percentage points and a drop in the probability of attending college with 1.1 percentage points. Thus, the impact of parental employment protection on child development does not only affect the quality of the human capital that children accumulate, but also the quantity.

Fourth, we show that the timing of parental enrollment in these programs seem to matter for how they impact child development. Specifically, enrollment that takes place closer to the time when the education outcomes are measured have larger impacts. While these differences are not always statistically significant across ages, these results are suggestive of a pattern similar to that found in prior work on the timing of large unexpected household shocks on children (e.g., Carneiro et al. (2022)).

Finally, in terms of mechanisms, we find that sick leave enrollment leads parents to be more likely to exit the workforce and earn lower wages, both in the short run as well as in the long-run (5 years after assignment). In addition, we find that parents become more dependent on the social safety net, and that there is a large positive effect on the total amount of welfare benefits transferred to the parent from the government in the long-run (though this effect is smaller than the negative earnings effect). We hypothesize that these adverse effects on labor market outcomes and welfare dependence, in combination with any potential negative role model and perception effects, are driving the effect on the human capital development of children. An interesting observation from our analysis is that the effect on children are larger if take-up is closer to the time when the education outcomes are measured rather than if take-up occurs in the early period of the child's life. The effects are therefore unlikely to be driven exclusively by welfare dependence and income effects (as this would imply larger effects for younger children who are exposed to these effects for a longer time), and at least partly driven by more short-run effects on components such as role model perceptions and stress.

The results from our analysis demonstrate that conventional social protection policies designed to help individual workers can cause negative spillovers to their children, and have important policy implications. First, the results highlight that the trade-off between social protection and work incentives extends beyond the individual worker. Second, it showcases the relationship between existing social institutions and child development, and highlights another dimension of the home environment through which children's human capital is shaped. Third, it implies that the costs of these programs are considerably larger than previously thought.

The main contribution of this paper is to exploit exogenous variation in the parental take-up of a key employment protection program and employ the full power of the Norwegian register data to identify its effect on the human capital development of children across their childhood. We contribute to the existing literature in five distinct ways. First, there is a well-established literature on the life-cycle approach to skill formation, focusing on the interaction between parental investments and childhood development (e.g., Heckman (2007)). A core focus of this literature has been to understand how susceptible children are to household-level shocks, variation in family resources, and changes in parental influences (e.g., Carneiro et al. (2022; 2021); Tungodden and Willen (2022)). However, none of these papers have explored how core employment protection policies implemented in the overwhelming majority of countries across the globe, such as sick leave, help or harm children. This paper advances our understanding of the interactions between existing social institutions and childhood development, highlighting the importance of how social institutions designed for a specific group of individuals may have unintended adverse effects on another group of individuals.

Second, central to the child development literature is the idea that there may be critical periods of learning during childhood in which children are more susceptible to adverse events (e.g., Knudsen et al. (2006); Cunha et al. (2006); Heckman and Mosso (2014)). A burgeoning literature in labor economics supports this hypothesis (e.g., Carneiro et al. (2021; 2022)). We push the boundaries of this literature by examining how access to worker welfare programs translate into effects on children across their childhood.

Third, there are a few papers examining the direct impact of sick leave on individual workers (e.g., Markussen (2012); Fevang et al. (2014); Markussen and Roed (2017); Pichler and Ziebarth (2020); Godoy and Dale-Olsen (2018)). However, none of these studies have been able to exploit random variation in sick leave enrollment.[2] In addition, no study has been able to exploit the impact of sick leave on child development. As one of the largest employment protection programs in the world, constituting the overwhelming majority of lost work days across the globe (Godoy and Dale-Olsen (2018)), understanding the full effect of the program on workers and their families is imperative. This paper moves us closer to achieving this goal.

Fourth, there is a wealth of observational studies on the effects of parental welfare utilization on children (see, for example, Black and Deveraux (2011), for an overview of these studies). However, many of these studies suffer from lack of exogenous variation in parental welfare enrollment, having to rely on fixed effects models with non-random variation in take-up (e.g., Bratsberg and Roed (2015)). While a handful of studies have moved beyond the observational study design and exploited quasi-experimental variation, these papers have been forced to exploit variation across geography and time (e.g., Antel (2021); Levine and Zimmerman (1996)). Using conditional random assignment to GPs and exploiting a GP leniency design, we advance this literature by providing carefully estimated and causally identified effects of parental welfare on children.

Finally, there is a small but extremely interesting literature focusing on the intergenerational dependence of specific welfare programs, such as disability insurance (Dahl and Gielen (2021)) and the U.S-specific anti-poverty programs AFDC, TANF, and EITC (Hartley et al.

[2]The one exception is Godoy and Dale-Olsen (2018); a fascinating paper that uses GP swaps in Norway to look at spillover effects of sick leave among colleagues at the workplace. However, this project is addressing a very different question, and their identification approach is different as they do not account for previous GP fixed effects.

(2017)). We contribute to this literature by providing a comprehensive account of the channels through which these effects may operate, exploring the full impact of parental welfare usage on child educational outcomes, both on the intensive as well as the extensive margin.[3] In addition, the shocks we explore are less extreme, much more common, and intended as much more of a temporary relief relative to programs such as disability insurance. Specifically, certified sick leave days make up the overwhelming majority of lost work days across the globe (Godoy and Dale-Olsen (2018)). Thus, sick leave is used by a significantly broader worker base and is the first instance of employment protection against health challenges before eventually having to resort to welfare programs of a more permanent nature.

The rest of this paper proceeds as follows: In Section 2, we provide institutional background. In Section 3, we introduce our data and empirical method. In Section 4, we present the main results from our analysis. In Section 5, we conclude.

2 Background

In this section, we briefly discuss employment relations and labor market protection in Norway. We also provide an overview of the most relevant aspects of the Norwegian welfare state, the GP system, and the education system, as it relates to the current analysis.

2.1 The Norwegian Welfare State and Paid Sick Leave

The Norwegian welfare model is based on the notion of universal access and encompasses universal healthcare, comprehensive social insurance, and free education through college.

All permanent residents of Norway are automatically enrolled in the public social security system, known as the National Insurance Scheme. This system is financed through a national insurance contribution imposed on both employers and employees. The system encompasses several welfare programs ranging from old age pension and health-related social insurance to transitional benefits for survivors and funeral grants. The three largest work-related social insurance programs are Unemployment Insurance (UI), Sick Leave (SL), and Disability

[3] In addition, our findings contribute to a long-standing debate on the intergenerational transmission of human capital and how to facilitate upward socioeconomic mobility (e.g. Black et al. (2005)).

Insurance (DI).[4]

The system for paid sick leave, which is the focus of this paper, is designed to provide compensation for income loss caused by a temporary illness or injury.[5] The replacement rate is 100 percent from the first day of leave subject to a maximum amount ($62,000 per year in 2019). To qualify for SL benefits, an individual must have been employed for the past four weeks. Sick leave beyond three days requires a certificate from the worker's GP.[6]

After the sick leave period expires, individuals can apply for work assessment benefits, a time-limited extension to sick leave (but with benefits reduced from 100 to 66 percent) intended to provide support for rehabilitation and rest to facilitate reintegration into the labor market.[7]

The two largest non-SL employment protection programs in Norway are UI and DI, and we explore spillover effects across these programs when studying the mechanisms behind our reduced-form effects. UI is available to all individuals who experience at least a 50 percent reduction in work hours and have a minimum income before becoming unemployed (Johnsen et al. (2022)). The replacement rate is approximately 62 percent, and the standard entitlement period is 104 weeks. The rules are more generous for older workers, and every worker over 60.5 is effectively entitled to UI until the mandatory retirement age of 67.

DI is provided to those who experience an injury or disability that causes a permanent reduction in earnings capacity. For the vast majority, the route to DI benefits goes through one year of sick leave and one-two years of work assessment benefits. To receive DI benefits, a doctor must certify that the individual has attempted all appropriate treatments that could help improve their work ability. The DI replacement rate depends on an individual's pre-DI

[4] In terms of employment protection, Norway has a medium-to-high degree of protection relative to other OECD countries (Huttunen et al. (2011)).

[5] SL benefits are paid by the employer for the first 16 days, and then by the government for a maximum of 52 weeks.

[6] In the public sector, workers can use 8 days of sick leave before having to obtain a certificate from the GP. However, the effects are relatively similar across the public and the private sector (see Section 5 for results and discussion). If the injury is related to the muscularskeletal system, the individual can also obtain approval from a chiropractor or manual therapist. We abstract from this in the current analysis, something that would attenuate our results.

[7] Before 2010, this was called rehabilitation benefits in the Norwegian system.

earnings. Specifically, while the after-tax replacement rate can be above 100 percent for low-income groups, it decreases at higher incomes. The after-tax replacement rate for fully disabled, previously average earners, is around 65 percent (Blondal and Pearson (1995)).

2.2 The Norwegian GP System

The Norwegian health care system is a two-part system, with primary care provided by the local municipalities and specialist care provided by larger health regions. This is similar to most countries in Europe. Access to specialist care and hospitals is only possible through referrals from GPs in the primary care sector (except in emergencies). The GP is therefore the first point of contact for non-emergency and preventive care, and is responsible for initial examination, diagnosis and treatment.

In terms of the primary care system, every Norwegian resident is assigned a general practitioner by the Norwegian Health Economics Association (part of the Norwegian Directorate of Health). In general, individuals must interact with their assigned GP every time they use the health care system. However, if the GP has already referred the patient to a specialist for a specific illness or problem, the patient may continue to use the specialist for that specific purpose without going through the GP. Individuals are allowed to change the GP they have been assigned twice a year conditional on availability (Riise et al. (2022)).

GPs are traditionally self-employed, and municipalities contract with individual GPs to provide services to their local residents by assigning them a patient list.[8] GP earnings come primarily from fee-for-service from the health administration (around 70 percent), but also from capitation from the municipalities (30 percent) and out-of-pocket payments from patients. GPs are well paid relative to other professions in Norway, with the average GP making around $100,000 per year (Ginja et al. (2022)).

In the current analysis, we require variation in GP assignment that is orthogonal to other patient characteristics. To this end, we exploit the fact that patients are randomly

[8]In recent years, an increasing share of GPs have been hired directly by the municipality governments on a permanent contract. As of 2021, this share was 14 percent.

reassigned to new GPs in the municipality (conditional on availability) when their current GPs retire, move, or for some other reason decide to terminate/reduce their current practice. As described in Riise et al. (2022), there are two important aspects of this process. First, in the event of list reductions, which patients to be removed from the list must be randomly determined. Second, in the event of reassignment, patients are randomly assigned to new GPs in the municipality conditional on availability.

To causally identify sick leave leniency, we exploit GP reassignments induced by GP retirement or other causes that are outside the patient's and the new GP's control as a source of exogenous variation in doctor-patient match. We do not use the initial assignments, nor any swaps initiated by the patients, due to endogeneity concerns. In addition, we always include pre-reassignment GP fixed effects, such that our leniency measure is identified off of patients who initially had the same GP but then are exogenously allocated to new, and different, GPs. It is worth noting that in certain cases, entering GPs can take over the entire list from a retiring GP. Thus, should a new GP take over the entire patient list of a retiring GP, those patients will not contribute to our identification due to pre-reassignment GP fixed effects.

2.3 The Norwegian Education System

The Norwegian education system encompasses ten years of mandatory education starting at age 6. The curricula is set by the central government and the overwhelming majority of children attend public primary school (>95 percent).

Following the completion of compulsory education at grade 10, each student has the right to enroll in tuition-free high school (conditional on satisfactory graduation from compulsory school). The majority of Norwegian children pursue this option, but in contrast to many other countries, high school is not mandatory.

High school in Norway consists of several program specializations within two types of tracks: an academic track and a vocational track. Students apply to high school through a centralized online system with the grades from their final year of compulsory education at the age of 15. The application consists of ranking three program specializations in the county of residence.[9] If the number of applications exceeds the number of available slots for a given program specialization, students will be assigned based exclusively on their grades in compulsory school.

High school education provides the student with university admission certification, vocational competence, or basic (craft) competence. University admission certification permits individuals to apply to, and enroll in, college. While university admission certification is awarded automatically to all students who complete the academic high school track, individuals in the vocational track must take supplemental courses to attain this qualification.

Higher education in Norway is offered by a range of universities and colleges, the majority of which are tuition-free public institutions. Admission is coordinated through the Norwegian Universities and Colleges Admission Service. Students apply to specific programs at the different universities, and if the number of applications exceeds the number of available slots for a given program, students will be assigned exclusively based on their grades in high school. Admission to university is conditional on having graduated from high school with a university admission certification.[10]

3 Data

In this paper, we exploit conditional random assignment of GPs coupled with detailed patient data to construct a sick leave leniency measure that is orthogonal to other patient characteristics that may independently impact the outcomes we are interested in. We link patients to their children through multi-generational family registers and collect detailed educational data throughout the children's upbringing. Finally, we combine these data with detailed labor market and welfare usage information on the parents themselves to study

[9] During our analysis period, Norway is divided into 19 administrative regions, called counties. The counties form the primary first-level subdivisions of Norway and are further divided into 431 municipalities. In 2020, the number of counties was reduced to 11, and the number of municipalities was reduced to 356. However, this does not coincide with our sample period.

[10] In addition, some programs impose specific course requirements such that only individuals who have taken certain high school courses are eligible for admission.

potential mechanisms.

The analysis performed in this paper requires linkages across several administrative data sets, and the data we use come from rich population-wide registers covering the universe of Norwegian residents and their health, education, and labor market histories. In this section, we carefully outline each of these data sources and provide details on how they are used in our final analysis. In terms of time period, we use exogenous swaps that occur in the years from 2006 to 2018, the time frame for which we have outcome data and information on GP assignments.

3.1 GP and Health Data

The Norwegian GP register provides information on the universe of all active GPs in the country for each year. Using unique GP identifiers, we combine this data with information from the Control and Payment of Health Refunds Database, which provides data on the number of times each patient has met the GP, the reason for the visit, the tests and examinations performed during the visit, and the outcome of the visit. Importantly, these data also contain information on whether the GP has provided the patient with a sick leave certificate, effectively activating the release of sick leave pay from the state and allowing the patient to be absent from work. In addition, these data contain information on the number of sick leave days that the patient has qualified for and used.

Crucial to our analysis is the ability to obtain conditionally random variation in GP assignment across otherwise similar patients. To achieve this goal, we exploit the fact that the GP data also provide information on whether an individual changed GP during the year and the reason for that change. For our project, we are interested in GP changes that are outside the patient's control, which generates plausibly exogenous variation in the leniency of the patient's new GP. To this end, we focus on GP changes that are caused by the doctor deciding to terminate, or significantly reduce, her patient list. List terminations are primarily driven by GPs retiring or moving. In Section 4, we provide evidence consistent with the notion that patient characteristics, as well as GP quality, are uncorrelated with the leniency of the newly assigned GP.

3.2 Child Education Data

Crucial to our analysis is the ability to link patients to their children, something we do through a unique family identifier. By following these children over time, from compulsory school into college, we can examine the impact of parental sick leave take-up on children's short-and long-run education outcomes, both overall and as a function of the child's age at the time of GP change.

In terms of outcomes, we focus on a broad range of educational outcomes: GPA at the end of compulsory school (grade 10), high school GPA, the probability of pursuing an academic high school track, graduating from high school, and starting college. Summary statistics of these variables are provided in Panel A of Table 1. Taken together, these outcomes allow us to obtain a comprehensive understanding of the impact of parental employment protection take-up on children's educational outcomes in terms of performance, attainment, and behavior – both on the intensive as well as the extensive margin.

3.3 Labor Market and Welfare Data

To understand the mechanisms through which the child development effects operate, we follow parents across the administrative registers and collect key labor market and welfare information. These data are obtained from the tax authority and the social insurance database, and provide detailed information not only on the employment and wages of individuals, but also on all welfare programs they are enrolled in and for what period. These data thus allow us to investigate if paid sick leave affects the employment, wage, and welfare dependence of the parent, and the extent to which these channels explain the child effects we observe.

In terms of outcomes, we begin by examining the effect of leniency on wages and employment. Our wage measure is based on pre-tax labor earnings (including income from self-employment) excluding government transfers. An individual is considered employed if she has positive income in a given year. In addition to the employment and wage outcomes, we explore welfare dependence spillover effects to the main employment protection programs discussed above: DI and UI. Summary statistics of these variables are provided in Panel B of Table 1.

It is worth noting that there are a number of smaller welfare programs and support systems in Norway as well, all of which could be implicated by the sick leave effects we identify (e.g., housing support and social assistance). To ensure that we identify the total effect of sick leave leniency on welfare dependence, we therefore also estimate the impact of leniency on the total welfare transfers from the government to the parent.

4 Method

4.1 Measure of sick leave leniency

To construct our measure of GP leniency, we exploit a unique aspect of the Norwegian health care system in which patients are conditionally randomly allocated to new GPs in the event their current GP closes down or significantly reduces their practice. This allows us to obtain a measure of leniency that is orthogonal to any patient characteristics that may impact the child human capital development outcomes we explore. It should be noted that we restrict our sample to parents who were employed at the time of the exogenous GP swap, as sick leave certification is conditional on having worked for the four weeks leading up to the sick leave request (see section 2). We estimate the following equation:

$$h_{ijkt} = \mu_j + \pi_k + \boldsymbol{\theta_{it}} + \varepsilon_{ijkt}, \tag{1}$$

where h_{ijkt} represents the number of sick days of patient i in the year after exogenous assignment to GP j from GP k at time t. $\boldsymbol{\theta_{it}}$ is a vector of controls for year-at-swap, age-at-swap, sex, and sick leave before swap (dichotomous); π_k are pre-swap GP fixed effects; and μ_j represent the exogenously-assigned new GP fixed effects. The new GP fixed effects μ_j form the basis of our leniency measure.[11] The inclusion of pre-swap GP fixed effects in

[11]We do not directly include municipality fixed effects as they are almost perfectly absorbed by the

Equation 1 means that the leniency measure is identified off of a set of patients who had the same initial GP but then were randomly allocated to new and different GPs due to factors orthogonal to their health characteristics and the newly-assigned GP's quality. Thus, should a new GP take over the entire list of a retiring GP, those patients would not contribute to our identification.

It is important to note that we require physicians to be connected to each other through the patients they treat. Specifically, as illustrated by Abowd, Kramarz, and Margolis (1999), the pre-swap GP fixed effects and the exogenously-assigned GP fixed effects are only separately identified within connected sets of GPs. These GPs would be connected by patients from each pre-swap GP having different exogenously-assigned GPs (which is part of the research design) and by exogenously-assigned GPs who receive patients from multiple pre-swap GPs. To this end, we restrict our analyses to the largest connected group (this group includes 99 percent of all patients in our sample). To define our connected sets of GPs, we use all patients involved in exogenous GP re-assignments.

4.2 Estimating impact on children and parents

After obtaining estimates of GP leniency, we construct a continuous standardized (mean 0, SD 1) measure of leniency x_j based on μ_j from above. We then leverage this measure to examine the effect of parental sick leave on child human capital development (main research questions) as well as the effect of parental sick leave on own labor market and welfare outcomes (mechanisms investigation). We estimate versions of the following equation:

$$w_{ijkt} = \beta x_j + \pi_k + \boldsymbol{\theta_{it}} + \varepsilon_{ijkt}, \tag{2}$$

where β is the effect of a 1 SD increase in leniency and corresponds to the parent receiving two weeks of additional paid sick leave. Provided that there is no systematic allocation of patients to new GPs of different leniency, something which we discuss and provide support for in Table 2 below, Equation 2 enables us to estimate the causal impact of sick leave leniency

previous GP fixed effects.

on the outcomes of patients and their children. In the event that an individual experienced several different GP changes during the analysis period, we focus on the leniency of the first exogenous GP swap.

In the robustness and sensitivity section, we show results from a variety of alternative specifications, including (1) a version in which μ_j is based on a leave-one-out method in which we exclude individual i from the leniency calculation when examining the impact of GP leniency on individual i's outcomes, (2) a version in which we're accounting for potential sampling error through a shrinkage design, (3) a version in which we drop children who are exposed to the same exogenous GP swap as their parent, and (4) a version in which we restrict the sample to parents who use sick leave in the year before the swap. In addition, we show robustness of our results to altering the set of fixed effects and controls included in our main estimating equation through a specification curve, and we show that the results are robust to dropping individual years and counties. Our results are robust to all of these adjustment.

4.3 Identifying assumptions

The validity of our estimation framework hinges on the assumption that there is no systematic sorting of exogenously-assigned patients to GPs as a function of GP leniency. In theory, the validity of this assumption follows directly from the fact that the Norwegian Health Economics Administration randomly reassigns patients to new local GPs conditional on municipality and availability when their old GPs no longer are available. In practice, we can examine this in detail by showing that the leniency measure is unrelated to characteristics of patients that may also predict their children's human capital outcomes.

To this end, we conduct an extensive balancing test in which we regress our estimated leniency measure on a rich set of observable patient characteristics determined prior to the swap: age at swap, employment status, use of unemployment insurance benefits, use of disability insurance benefits, income, immigrant status, education, recent fertility, number of children, marital status, and spouse characteristics. Results from this exercise are provided in

Table 2. All coefficients are economically small and only 1 out of 14 estimates are marginally statistically significant.

In addition to the extensive balance test, one concern may be that more lenient GPs are of a different quality than less lenient GPs. If so, some of the effects we identify could operate through GP quality rather than GP leniency (GP quality affecting the health of the parent which could indirectly spill over to the child's human capital development). However, we find no statistically significant or economically meaningful relationship between GP leniency and short-and long-term mortality (Appendix Table A-1) at the patient level. In addition, we find no correlation between GP leniency and other GP characteristics at the doctor level, such as GP value-added, GP gender, and GP patient load (Appendix Table A-7).[12] Finally, we see no relationship between GP leniency and inpatient visits, ER visits, or the likelihood that the GP conducts check-ups with the patient (Appendix Table A-8). These results, in combination with the exogenous assignment mechanism and the rich set of fixed effects in our main specification, make it unlikely that the effects we identify are driven by anything other than GP sick leave leniency.

5 Results

In this section, we present our key findings on the effect of parental employment protection take-up on child human capital development. We begin by providing descriptive evidence on the distribution of sick leave and GP leniency in our setting. We then examine how parental take-up of sick leave, as a direct implication of being assigned to a more lenient GP, affects the human capital development of children. In this part of the analysis, we also show results on the timing of the parental employment protection take-up, demonstrating that the age of the child at the time of parental employment protection take-up matters. Finally, we turn to the parents themselves, examining how exogenous shifts in sick leave probability impact their future labor market outcomes and welfare dependency probabilities. This allows us to

[12] GP value-added is the 2-year post-assignment mortality of a GP's patients based on the conditional random assignment that we use for identifying leniency (see Ginja et al. (2022)).

better understand the mechanisms through which our child development effects operate.

5.1 Descriptive evidence on GP leniency

Figure 1 shows the variation in sick leave duration (Panel A) and GP leniency (Panel B) in the year following the exogenous assignment of patients to new GPs. Panel A illustrates that approximately 15 percent of our sample experiences a paid sick leave spell, and that there is substantial variation in the duration of paid sick leave conditional on receiving sick leave.

The median sick leave spell is around 90 days. Although shorter spells are more common, there is a substantial fraction of people who experience longer sick leave spells as well. For example, about 20 percent of individuals on sick leave experience between 90 and 180 days of paid sick leave, and 10 percent of individuals on sick leave experience between 180 and 270 days of paid sick leave. In addition, we see a non-trivial share of individuals bunching at the right-tail of the distribution (365 days); the maximum number of days of sick leave an individual can receive in a given year year.

The pre-standardized GP leniency measure, obtained through the estimation of μ_j in Equation 1, is shown in Panel B of Figure 1. The leniency measure approximates a normal distribution relatively closely, with a mean of 0.2 and a standard deviation of 11. The figure demonstrates that being assigned to a GP who is located 1 SD above the mean leniency generates an additional 4.5 weeks (or 22 days) of paid sick leave relative to being assigned to a GP who is located 1 SD below the mean leniency. This is a substantial amount, equivalent to slightly more than a month of full-time employment (or a 25 percent difference relative to the mean).

Figure 2 demonstrates that the variation in sick leave leniency is much more pronounced for hard-to-verify musculoskeletal and psychological causes for which GPs have more individual freedom to choose whether to grant sick leave or not, and is much less pronounced for causes with little room for subjective interpretations, such as circulatory and respiratory causes (Appendix Table A-6 provides a full list of leniency standard deviations by ICPC code). This is reassuring, as there is greater scope for variation in leniency for causes that are hard to verify.

5.2 Effects on human capital development of children

Overall effects. Our core results on parental employment protection take-up on child human capital development, obtained from estimation of Equation 2, are displayed in Table 3. The outcomes we examine are GPA at the end of compulsory school, high school GPA, the probability of pursuing an academic high school track, graduating from high school, and starting college. We include previous GP fixed effects in all our specifications. This means that we compare children of individuals who originally had the same GP, but that were reallocated to new – and different – GPs because of external factors outside their control.

The result in column 1 shows that children whose parents are exposed to a 1 SD more lenient GP experience a reduction in education performance in lower secondary school. This effect is both economically meaningful and highly statistically significant. In terms of magnitude, the point estimate implies that children whose parents are exposed to a 1 SD more lenient GP experience a reduction in lower secondary GPA by 3 percent of a standard deviation. This performance effect is relatively sizable and is likely to have implications for the children's labor market outcomes; especially in light of recent evidence connecting small GPA changes to large differences in employer's hiring interest (Kessler et al. (2019)) and callback rates (Quadlin (2018)).

In column 2, we examine the performance effect in upper secondary school. The point estimate in column 2 is very similar to that in column 1. The consistent performance effect across the different educational levels implies that the GPA effect identified in column 1 is not a short-term transitory effect, but likely a long-term permanent implication of parental welfare take-up.

The results in columns 1 and 2 are important for disentangling the theoretical ambiguity surrounding the impact of employment protection on child development. As noted in Section 1, employment protection take-up could benefit child development through a reduction in the financial impact of the shock on the household, as well as through a reduction in the stress and mental health burden associated with such events (something which both may facilitate a smoother transition back into the labor force after the shock as well as ensure stress-free and high-quality child-parent interactions during the shock). However, these programs may also hurt child development through increased welfare dependence, a negative impact on parents' long-run labor market trajectory, and negative role model/perception signals to the child. The results in columns 1 and 2 of Table 3 imply that the negative effects outweigh the positive, and that the overall effect on children's development is negative.

In addition to affecting the intensive margin of educational performance, parental welfare enrollment could impact both the quantity as well as the quality of the human capital investments that the children undertake. To this end, we also explore the impact on the type and quantity of education in high school (columns 3 and 4 of Table 3) and college (columns 5 and 6 of Table 3).

In terms of high school effects, columns 3 and 4 demonstrate that GP leniency is associated with a decline in the likelihood of graduating, but not with a change in the probability to select into the academic versus vocational track. This suggest that parental welfare take-up has an overall impact on the amount of human capital investment that children make, but not on the type of investment that they make (conditional on making those investments).

In terms of college effects, columns 5 and 6 show that GP leniency negatively impacts children's probability to enroll in college, and generates an overall decline in the years of education that the children complete. For example, in response to the parent being assigned a GP who is 1 SD more lenient, we find a reduction in the probability of attending college with 1.1 percentage points. Thus, the impact of parental employment protection on child development does not only affect the quality of the human capital that children accumulate, but also the quantity. These results are in line with the negative impact on high school graduation in column 4, as well as with the negative performance effects identified in columns 1 and 2.

Taken together, the results displayed in Table 3 highlight that the trade-off between social protection and work incentives extends beyond the individual worker, showcases the relationship between existing social institutions and child development, and demonstrates another dimension of the home environment through which children's human capital is shaped.

Timing effects. The life-cycle approach to skill formation suggests that children's development depends not only on how much investment occurs during their childhood, but also on its timing (e.g., Heckman (2007)). As such, exposure at key stages of development, for example close to when key educational choices are made and exams are taken, may be fundamentally different relative to exposure at other ages. To examine this question in detail, Table 4 provide evidence on the effect of GP leniency on a selection of short-run (GPA) and long-run (college enrollment) child educational outcomes as a function of the age of the child at the time of the parental sick leave take-up.

The results in Table 4 highlight that the timing of parental employment protection take-up matters for how it affects child development. Specifically, enrollment that takes place closer to the time when the education outcomes are measured have larger impacts. While the effects are often not statistically significant across ages, the monotonic increase in effect size is consistent with prior work on the timing of investment in children (e.g., Carneiro et al. (2021; 2022)), with exposure in early adolescence having a larger impact. These results suggest that the design of health, education, and welfare programs should consider that the value of insurance against shocks might vary substantially depending on the age of the children in the household, and that these timing effects do not necessarily coincide with previously documented critical learning periods (e.g., age 3 through 5).[13]

Heterogeneity effects. In light of recent literature documenting substantial effect heterogeneity in response to early childhood shocks across child sex, socioeconomic status, and

[13]Note that we have fewer observations for children who were of a very young age at the time of exposure (since we must wait at least until age 16 to collect outcome information on them). As such, it is problematic to split the sample into uniform age ranges (e.g., 3 year intervals). Instead, we have divided the sample into age groups such that the sample size is relatively stable across the groups while at the same time maintaining a meaningful age division. Because of this, the youngest age group encompasses many more ages, but still has a sample size that is slightly smaller.

parental sex, we perform a series of heterogeneity analyses to examine if certain children are more impacted by parental welfare take-up than others.

The results from this series of analyses are shown in Table 5 (parent sex), Table 6 (child sex), Appendix Table A-2 (child ability), Appendix Table A-3 (parental education), and Appendix Table A-4 (parental income). Overall, the heterogeneity analyses suggest that boys as well as children of lower baseline ability (as measured by performance on standardized tests prior to exposure) are slightly more impacted by parental welfare take-up. We find no systematic differences across parent sex or the socioeconomic condition of the household.[14]

5.3 Effect on parents labor market and welfare outcomes

After having estimated the sick leave leniency of GPs in Norway and explored the impact on child development, we proceed to investigate potential mechanisms that may explain the effects we observe. We do this by linking the patient data to a rich set of labor market and welfare participation information, enabling us to determine the impact of sick leave on the parents themselves – and through which of these channels the effect on children may operate.

We begin by examining the impact on earnings and employment, both in the year immediately following the exogenous GP swap (Panel A), as well as effects five years after (Panel B). The results from this analysis are provided in Table 7. Focusing on the short-term effects in Panel A, the result in column 1 shows that sick leave certification has no effect on the employment prospects of the individual worker in the first post-swap year. This is perhaps expected, as sick leave pay is conditional on employment.[15] In column 2, we show that the sick leave take-up generates a drop in individual earnings. This is most likely a mechanical relationship caused by the government-mandated cap on sick leave benefits (as discussed in section 2). However, this reduction is very modest at 1 percent of average worker earnings. In terms of the long-run effects shown in Panel B, the results tell a consistent, but slightly

[14] As noted in Section 2, in the public sector, the rules are slightly more generous then in the private sector. As such, we also conducted a stratified regression based on which sector the parent worked in. However, the effects are relatively similar across the public and the private sector (Appendix Table A-5). This suggests that the effects are not exclusively loading on one particular sector that has different types of rules.

[15] An individual on sick leave remains formally employed by the firm.

different, story. Specifically, in the long-run, we observe a statistically significant and economically meaningful negative effects on employment, and much larger negative effects on earnings. This is a noteworthy result, suggesting that the temporary sick leave program appears to generate persistent and long-lasting negative labor market effects among individuals who were assigned to a more lenient GP relative to a less lenient GP.

To examine if there are any program substitution effects into the two largest non-sick leave welfare programs in Norway – UI or DI – we estimate the effect of GP leniency on take-up of UI and DI. We focus this analysis on effects five years after the swap; spillover potential is limited in the first post-swap year, especially since the individuals may still be on sick leave at that time (and do not yet qualify for DI). As noted in section 2, there are a number of smaller welfare programs and support systems in Norway as well, all of which could be impacted by the sick leave effects we identify (e.g., housing support and social assistance). To ensure that we identify the total effect of sick leave leniency on welfare dependence, we therefore also estimate the impact of GP leniency on the total welfare transfers from the government to the parent.

The results from this analysis are provided in Table 8. While we see no effect on UI take-up (column 1), we see large cross-program substitution to DI (column 2). DI substitution is likely driven by individuals who have exhausted the sick leave benefits, and meet the requirements to qualify for DI. In column 3, we summarize the impact on welfare transfers from the government by showing the effect of leniency on the total amount of government transfers received by the parent. The result demonstrates a significant positive effect on this dimension, though this effect is not sufficiently large to completely offset the income loss shown in column 2 of Table 7. Specifically, the result in column 3 suggest that the increased welfare usage can mute approximately 25 percent of the overall long-term income loss caused by GP leniency.

Taken together, the results in Tables 7 and 8 demonstrate that sick leave enrollment leads parents to be more likely to find themselves outside the workforce, earn lower wages, and become more dependent on the social safety net. We hypothesize that these adverse effects, in combination with any potential negative role model and perception effects, are driving the effect on the human capital development of children. An interesting observation is that the effect on children are larger if take-up is closer to the time when the education outcomes are measured rather than if take-up occurs in the early period of the child's life. The effects are therefore unlikely to be driven exclusively by welfare dependence and income effects (as this would imply larger effects for younger children who are exposed to these effects for a longer period of time), and at least partly driven by more short-run effects on components such as role model perceptions and stress.

5.4 Robustness and sensitivity

To ensure that our results are not driven by particular features of our research design, we conduct a series of robustness and sensitivity analyses on our main findings. The main results from these analyses are provided in Table 9. To facilitate the interpretation of these results, Panel A show our main results for comparison purposes.

First, we perform a leave-one-out extension of the design. We conduct this analysis to avoid a mechanical relationship between our leniency measure and the child outcomes we investigate. To this end, we adjust Equation 1 such that the estimation of μ_j is based on a leave-one-out method in which we exclude individual i from the leniency calculation when examining the impact of GP leniency. This provides us with a measure of GP leniency that is independent of the individual patient whose outcomes we are examining. The results from this analysis are provided in Panel B of Table 9. While the effects become slightly smaller in magnitude, they remain highly statistically significant and economically meaningful.

Second, one challenge with estimating μ_j is sampling error because each GP has a different number of patients for which we can calculate leniency. It is perhaps less of a concern in our setting setting given the number of patients per GP, but it may still generate non-negligible variation in the degree of certainty associated with leniency across GPs. To examine if this has an impact on our results, we follow Chetty et al. (2014) and construct a Bayesian empirical estimator by adjusting the estimated leniency.[16] The results from this analysis are provided in Panel C of Table 9. The effects become slightly larger in magnitude after adjusting for potential sampling error, but provide strong support for our core results discussed above.

Third, one concern with using exogenous GP swaps is that children may swap GP at the same time as the parent. In such cases, the effects we identify on child development could be driven by the direct impact of the GP leniency on the child, rather than through the effect of the GP leniency on the parent. To this end, we estimate Equation 2 using only children who do no experience the same exogenous swap as the affected parent. The results from this analysis are provided in Panel D of Table 9. Our results are unaffected by this adjustment.

Fourth, we note that parents who have not used sick leave earlier in their career are less likely to request sick leave certifications from new GPs than parents who have used sick leave earlier in their career. The presence of such never-takers may bias our results towards zero. To this end, we estimate Equation 2 using only parents who had been taking some type of sick leave in the year before the swap. This allows us to zoom in on the individuals that we believe are more likely affected by the leniency of the GPs that they are assigned. The results from this analysis are provided in Panel E of Table 9. Overall, most of the point estimates become larger than our baseline results, though the main take-away from the analysis remain unaffected.

In addition to the above analyses, we have also estimated the sensitivity of our results to different compositions of controls, restricting the sample to the common support of a propensity score matching algorithm, and estimating standard errors based on random inference. The results from these exercises are shown in Table 10. None of these exercises produce results that deviate from our main findings.

Finally, we have estimated our main equation, sequentially eliminating specific counties

[16] Specifically, we estimate $BE_j = \lambda_j Leniency_j$, where the shrinkage factor is $\lambda_j = \sigma_\mu^2/(\sigma_u^2 + \sigma_\epsilon^2/\eta_j)$. The term σ_u^2 represents the between-GP variation in the given outcome and σ_ϵ^2 is the within-GP variance in the given outcome. In other words, we take advantage of the fact the we observe the full load of patients for a GP in order to account for potential sampling error.

and years from the analysis. The idea behind this exercise is to ensure that our results are not driven by a particular year or region of the country. The results from these analyses are provided in Appendix Figures A-1 and A-2. These figures suggest that the results are not driven by particular regions or years.

6 Conclusion

Children are highly susceptible to their home environments, and a rich literature has demonstrated how the structure and resources of families influence the human capital development of children. Employment protection and social security programs that shield children from abrupt changes to the home environment may therefore play an important role in their human capital advancement.

This paper uses conditional random assignment of patients to GPs to calculate a leniency measure of paid sick leave certification. We link these data to information on the human capital development of the patients' children. We find sizable negative effects of parental sick leave enrollment on the child's human capital development. In addition, we show that the timing of parental enrollment in these programs matter; enrollment closer to when the education outcomes are measured have larger impacts.

In terms of mechanisms, we find that sick leave enrollment induces parents to be more likely to find themselves outside the workforce, earn lower wages, and become more dependent on the social safety net.

The main contribution of this paper is to exploit exogenous variation in parental take-up of a key employment protection program that accounts for the overwhelming majority of lost work days across the globe and leverage the full power of the Norwegian register data to identify its effect on the human capital development of children across their childhood.

The results from this analysis have important policy implications, demonstrating that conventional social protection policies designed to help individual workers generate negative spillovers to their children. First, the results highlight that the trade-off between social protection and work incentives extends beyond the individual worker. Second, it showcases the relationship between existing social institutions and child development, and highlights another dimension of the home environment through which children's human capital is shaped. Third, it implies that the costs of these programs are considerably larger than previously thought.

While our results provide strong suggestive evidence on the mechanisms through which these effects operate, we consider it an important direction of future research to disentangle the relative magnitude of the various mechanisms we explore. This will help us better understand how we can design employment protection systems in the future that benefit workers while at the same time inflict minimum damage on the human capital development of the recipients' children.

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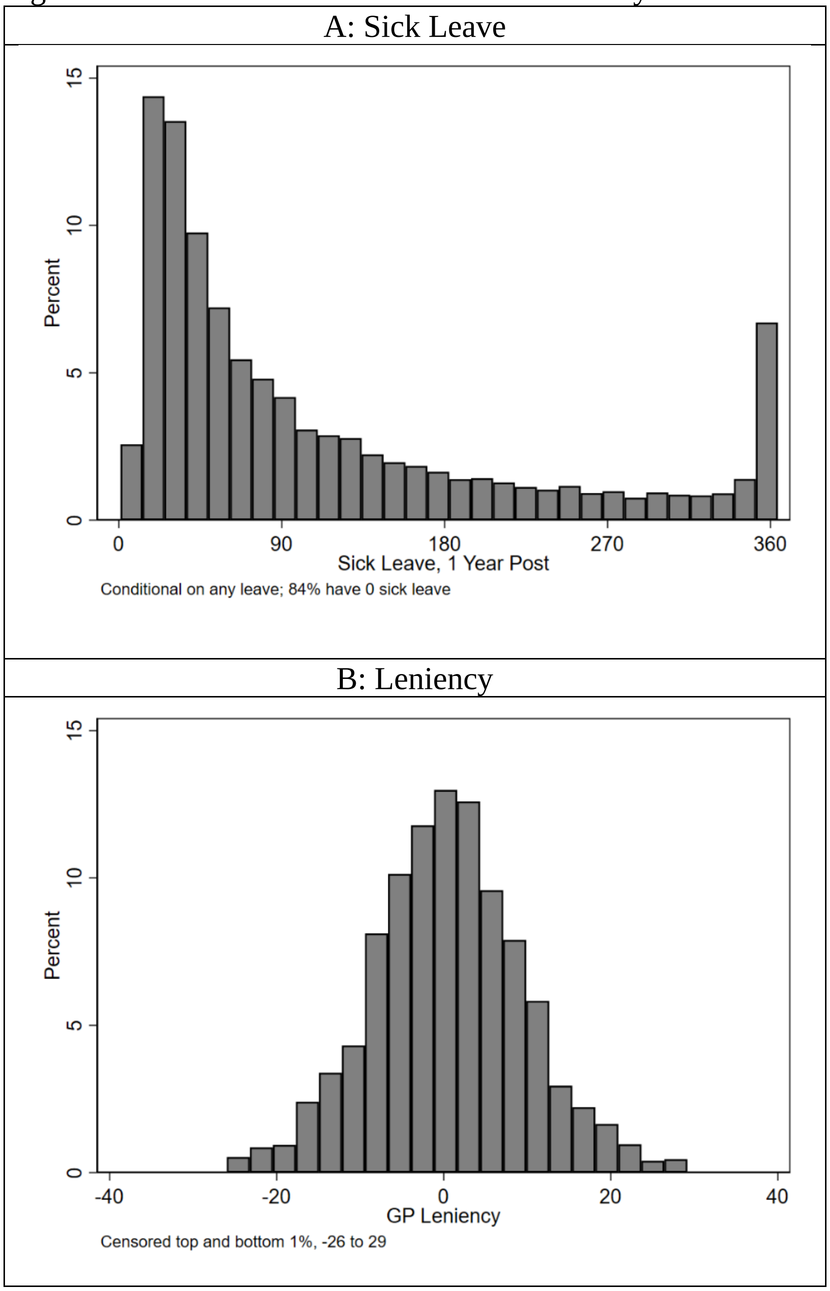
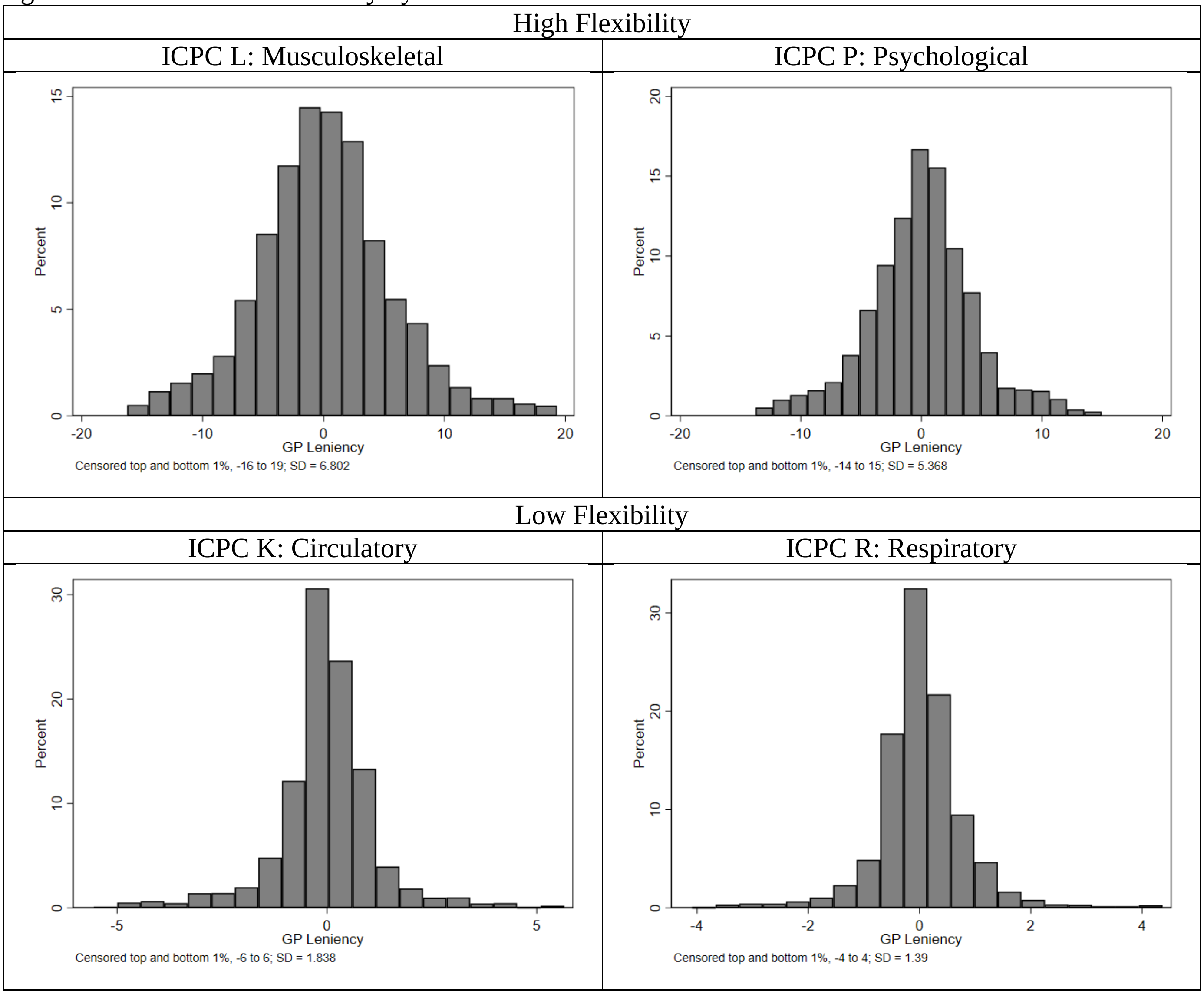
Figure 1: Distribution of Sick Leave and Leniency



Note: Panel B displays the unstandardized sick leave leniency measure, which has a mean of 0.2 standard deviation of 11.0 days.

Figure 2: Distribution of Leniency by Sick Leave Reason



Note: Categories are based on the International Classification of Primary Care, 2nd edition.

Table 1: Summary Statistics

	Mean	SD	N
Child Variables			
GPA, Grade 8-10	4.139	0.819	312,357
GPA, Grade 11-13	3.988	0.875	459,004
Academic Track	0.743	0.437	256,157
HS Grad	0.653	0.476	322,395
Start College	0.614	0.487	451,122
Years of Ed	12.626	1.925	322,395
Parent Variables (1 Year Post)			
Sick Leave	18.4	61.5	211,606
Employed	0.980	0.139	211,606
Earnings	528531	403026	211,606
Any UI	0.047	0.211	211,606
Any DI	0.020	0.14	211,606

Table 2: Balance Test

	Age	Employed	Any UI	Any DI	High Earnings	Norwegian	High Edu
Leniency SD	-0.000	0.001	0.001	0.000	-0.003	-0.002	-0.006*
	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Dep Mean	42.824	0.847	0.039	0.167	0.500	0.849	0.738
Dep SD	6.572	0.360	0.194	0.373	0.500	0.358	0.440
N	214,727	214,727	214,727	214,727	214,727	214,727	213,124

	New Birth	Total Children	Married	Spouse Age	Spouse Emp	Spouse Any UI	Spouse Any DU
Leniency SD	-0.001	0.006	-0.001	-0.024	0.001	0.002	0.001
	(0.001)	(0.004)	(0.003)	(0.025)	(0.002)	(0.002)	(0.001)
Dep Mean	0.022	2.118	0.619	43.957	0.596	0.040	0.019
Dep SD	0.146	1.237	0.486	6.547	0.491	0.196	0.135
N	214,727	214,727	185,132	138,462	214,727	127,780	127,780

Note: * $p<0.05$, ** $p<0.01$, *** $p<0.001$.
The table presents the OLS estimates of the effect of GP sick note leniency. Estimating equation: $w_{ijkt} = \beta x_j + \pi_k + \boldsymbol{\theta}_{it} + \varepsilon_{ijkt}$, where w_{ijkt} is the outcome at the top of the column, x_j is a standardized continuous measure of GP sick note leniency, π_k are previous GP FE, and $\boldsymbol{\theta}_{it}$ is a vector of controls (sick leave days the year before swap, patient age, and patient sex). Displayed estimates are the coefficient β, the effect of a 1 SD increase in GP sick note leniency.
Standard errors in parentheses clustered at GP level.

Table 3: Effect on Childhood Educational Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	GPA, Gr 8-10	GPA, Gr 11-13	Academic Track	HS Grad	Start College	Years of Ed
Leniency SD	-0.022***	-0.020***	-0.002	-0.012***	-0.011***	-0.049***
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.009)
Dep Mean	4.139	3.988	0.743	0.653	0.614	12.626
Dep SD	0.819	0.875	0.437	0.476	0.487	1.925
N	312,357	459,004	256,157	322,395	451,122	322,395

Note: * p<0.05, ** p<0.01, *** p<0.001.
The table presents the OLS estimates of the effect of GP sick note leniency. Estimating equation: $w_{ijkt} = \beta x_j + \pi_k + \boldsymbol{\theta_{it}} + \varepsilon_{ijkt}$, where w_{ijkt} is the outcome at the top of the column, x_j is a standardized continuous measure of GP sick note leniency, π_k are previous GP FE, and $\boldsymbol{\theta_{it}}$ is a vector of controls (sick leave days the year before swap, patient age, and patient sex). Displayed estimates are the coefficient β, the effect of a 1 SD increase in GP sick note leniency.
Standard errors in parentheses clustered at GP level.

Table 4: Effect Variation by Age of Exposure, Lower Secondary GPA and Start College

Panel A: Lower Secondary GPA

	(1)	(2)	(3)	(4)
	Age 3-8	Age 9-11	Age 12-14	Age 15-16
Leniency SD	-0.017*	-0.023**	-0.024***	-0.030***
	(0.008)	(0.007)	(0.007)	(0.007)
Dep Mean	4.225	4.159	4.125	4.094
N	52,297	72,823	101,885	83,452

Panel B: Start College

	(1)	(2)	(3)	(4)
	Age 3-8	Age 9-11	Age 12-14	Age 15-16
Leniency SD	-0.010	-0.016**	-0.016***	-0.019***
	(0.008)	(0.005)	(0.004)	(0.005)
Dep Mean	0.504	0.529	0.558	0.571
N	13,759	47,065	78,829	69,166

Note: * p<0.05, ** p<0.01, *** p<0.001.

The table presents the OLS estimates of the effect of GP sick note leniency. Estimating equation: $w_{ijkt} = \beta x_j + \pi_k + \boldsymbol{\theta_{it}} + \varepsilon_{ijkt}$, where w_{ijkt} is the outcome at the top of the column, x_j is a standardized continuous measure of GP sick note leniency, π_k are previous GP FE, and $\boldsymbol{\theta_{it}}$ is a vector of controls (sick leave days the year before swap, patient age, and patient sex). Displayed estimates are the coefficient β, the effect of a 1 SD increase in GP sick note leniency.

Standard errors in parentheses clustered at GP level.

Table 5: Effect on Childhood Educational Outcomes, by Parent Sex

Mother

	(1)	(2)	(3)	(4)	(5)	(6)
	GPA, Gr 8-10	GPA, Gr 11-13	Academic Track	HS Grad	Start College	Years of Ed
Leniency SD	-0.021***	-0.025***	-0.002	-0.011***	-0.011***	-0.039**
	(0.005)	(0.005)	(0.003)	(0.003)	(0.002)	(0.012)
Dep Mean	4.143	3.988	0.745	0.654	0.621	12.629
Dep SD	0.817	0.876	0.436	0.476	0.485	1.922
N	149,266	222,979	124,330	156,464	221,374	156,464

Father

	(1)	(2)	(3)	(4)	(5)	(6)
	GPA, Gr 8-10	GPA, Gr 11-13	Academic Track	HS Grad	Start College	Years of Ed
Leniency SD	-0.024***	-0.016**	-0.001	-0.013***	-0.010***	-0.057***
	(0.006)	(0.005)	(0.003)	(0.003)	(0.003)	(0.014)
Dep Mean	4.136	3.989	0.741	0.652	0.607	12.623
Dep SD	0.821	0.873	0.438	0.476	0.488	1.927
N	162,739	235,736	131,472	165,606	229,441	165,606

Note: * $p<0.05$, ** $p<0.01$, *** $p<0.001$.
The table presents the OLS estimates of the effect of GP sick note leniency. Estimating equation: $w_{ijkt} = \beta x_j + \pi_k + \boldsymbol{\theta_{it}} + \varepsilon_{ijkt}$, where w_{ijkt} is the outcome at the top of the column, x_j is a standardized continuous measure of GP sick note leniency, π_k are previous GP FE, and $\boldsymbol{\theta_{it}}$ is a vector of controls (sick leave days the year before swap, patient age, and patient sex). Displayed estimates are the coefficient β, the effect of a 1 SD increase in GP sick note leniency.
Standard errors in parentheses clustered at GP level.

Table 6: Effect on Childhood Educational Outcomes, by Child Sex

Girl

	(1)	(2)	(3)	(4)	(5)	(6)
	GPA, Gr 8-10	GPA, Gr 11-13	Academic Track	HS Grad	Start College	Years of Ed
Leniency SD	-0.022***	-0.016***	-0.001	-0.010***	-0.008***	-0.039***
	(0.005)	(0.005)	(0.002)	(0.003)	(0.002)	(0.012)
Dep Mean	4.363	4.131	0.823	0.736	0.713	12.960
Dep SD	0.776	0.858	0.382	0.441	0.452	1.787
N	151,944	224,522	134,958	156,633	228,384	156,633

Boy

	(1)	(2)	(3)	(4)	(5)	(6)
	GPA, Gr 8-10	GPA, Gr 11-13	Academic Track	HS Grad	Start College	Years of Ed
Leniency SD	-0.021***	-0.024***	-0.005	-0.015***	-0.015***	-0.062***
	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)	(0.013)
Dep Mean	3.927	3.851	0.654	0.575	0.513	12.310
Dep SD	0.801	0.869	0.476	0.494	0.500	1.996
N	159,930	234,009	120,749	165,340	222,273	165,340

Note: * p<0.05, ** p<0.01, *** p<0.001.
The table presents the OLS estimates of the effect of GP sick note leniency. Estimating equation: $w_{ijkt} = \beta x_j + \pi_k + \boldsymbol{\theta_{it}} + \varepsilon_{ijkt}$, where w_{ijkt} is the outcome at the top of the column, x_j is a standardized continuous measure of GP sick note leniency, π_k are previous GP FE, and $\boldsymbol{\theta_{it}}$ is a vector of controls (sick leave days the year before swap, patient age, and patient sex). Displayed estimates are the coefficient β, the effect of a 1 SD increase in GP sick note leniency.
Standard errors in parentheses clustered at GP level.

Table 7: Effect on Own Labor Market Outcomes, 1 and 5 Years

	(1)	(2)
Panel A: 1 Year Post Exposure		
	Employed	Earnings
Leniency SD	0.001	-4614**
	(0.001)	(1489.408)
Dep Mean	0.980	528531.454
N	211,606	211,606
Panel B: 5 Year Post Exposure	(1)	(2)
	Employed	Earnings
Leniency SD	-0.007***	-11285***
	(0.002)	(1940.661)
Dep Mean	0.945	551023.858
N	175,967	175,967

Note: * p<0.05, ** p<0.01, *** p<0.001.
The table presents the OLS estimates of the effect of GP sick note leniency. Estimating equation: $w_{ijkt} = \beta x_j + \pi_k + \boldsymbol{\theta_{it}} + \varepsilon_{ijkt}$, where w_{ijkt} is the outcome at the top of the column, x_j is a standardized continuous measure of GP sick note leniency, π_k are previous GP FE, and $\boldsymbol{\theta_{it}}$ is a vector of controls (sick leave days the year before swap, patient age, and patient sex). Displayed estimates are the coefficient β, the effect of a 1 SD increase in GP sick note leniency.
Standard errors in parentheses clustered at GP level.

Table 8: Effect on Own Social Safety Outcomes, 5 Year Post Exposure

	(1)	(2)	(3)
	Any UI	Any DI	Total Benefits
Leniency SD	0.001	0.008***	3128.8***
	(0.001)	(0.002)	(541.0)
Dep Mean	0.040	0.082	51786.8
N	175,967	175,967	175,967

Note: * p<0.05, ** p<0.01, *** p<0.001.

The table presents the OLS estimates of the effect of GP sick note leniency. Estimating equation: $w_{ijkt} = \beta x_j + \pi_k + \boldsymbol{\theta_{it}} + \varepsilon_{ijkt}$, where w_{ijkt} is the outcome at the top of the column, x_j is a standardized continuous measure of GP sick note leniency, π_k are previous GP FE, and $\boldsymbol{\theta_{it}}$ is a vector of controls (sick leave days the year before swap, patient age, and patient sex). Displayed estimates are the coefficient β, the effect of a 1 SD increase in GP sick note leniency.

Standard errors in parentheses clustered at GP level.

Table 9: Robustness to Sample

	(1)	(2)	(3)	(4)	(5)	(6)
	GPA, Gr 8-10	GPA, Gr 11-13	Academic Track	HS Grad	Start College	Years of Ed
Panel A: Main results						
Leniency SD	-0.022***	-0.020***	-0.002	-0.012***	-0.011***	-0.049***
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.009)
Dep Mean	4.139	3.988	0.743	0.653	0.614	12.626
N	312,357	459,004	256,157	322,395	451,122	322,395
Panel B: Leave one out (sick leave measure excludes parent *i*'s sick leave)						
Leniency SD	-0.013**	-0.014***	-0.000	-0.008***	-0.008***	-0.032***
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.009)
Dep Mean	4.139	3.988	0.743	0.653	0.614	12.626
N	312,357	459,004	256,157	322,395	451,122	322,395
Panel C: Shrinkage						
Leniency SD	-0.034**	-0.041***	-0.013*	-0.013*	-0.027***	-0.055*
	(0.011)	(0.009)	(0.006)	(0.006)	(0.005)	(0.026)
Dep Mean	4.139	3.988	0.743	0.653	0.614	12.626
N	312,352	459,002	256,156	322,390	451,117	322,390
Panel D: Drop children with same exogenous swap GP						
Leniency SD	-0.021***	-0.018***	-0.002	-0.012***	-0.011***	-0.048***
	(0.005)	(0.004)	(0.003)	(0.003)	(0.002)	(0.010)
Dep Mean	4.114	3.962	0.740	0.642	0.634	12.582
N	155,293	244,669	136,952	176,712	266,245	176,712
Panel E: Restrict to parents using sick leave year before swap						
Leniency SD	-0.042***	-0.034***	-0.001	-0.015**	-0.008	-0.060**
	(0.009)	(0.007)	(0.006)	(0.005)	(0.005)	(0.021)
Dep Mean	4.015	3.881	0.710	0.600	0.559	12.410
N	40,475	62,365	32,192	42,622	59,697	42,622

Note: * p<0.05, ** p<0.01, *** p<0.001.
The table presents the OLS estimates of the effect of GP sick note leniency. Estimating equation: $w_{ijkt} = \beta x_j + \pi_k + \boldsymbol{\theta_{it}} + \varepsilon_{ijkt}$, where w_{ijkt} is the outcome at the top of the column, x_j is a standardized continuous measure of GP sick note leniency, π_k are previous GP FE, and $\boldsymbol{\theta_{it}}$ is a vector of controls (sick leave days the year before swap, patient age, and patient sex). Displayed estimates are the coefficient β, the effect of a 1 SD increase in GP sick note leniency. Standard errors in parentheses clustered at GP level.

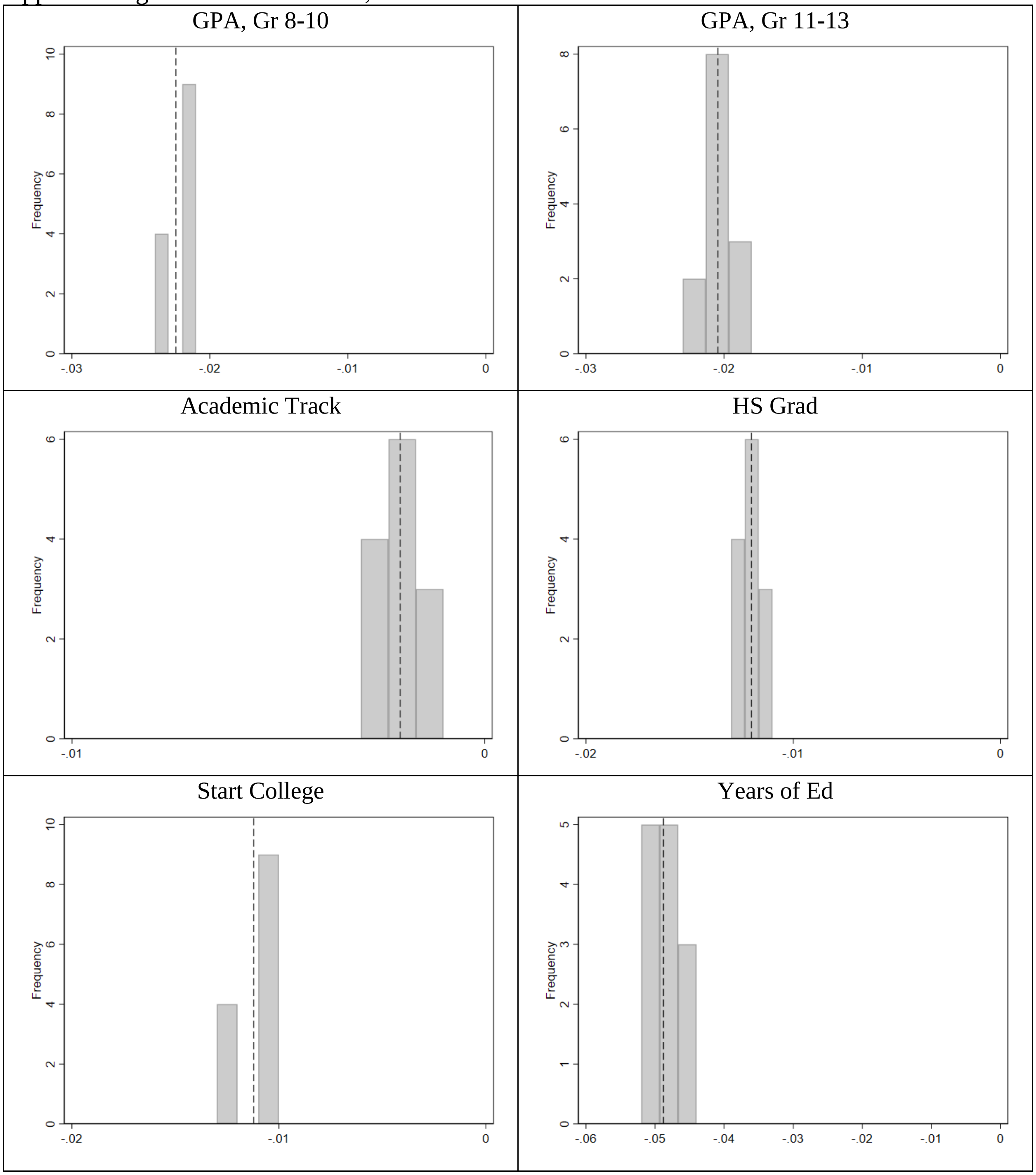
Table 10: Robustness to Model Specification, Random Inference

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Main	No Prev Sick Leave	No Parent Sex	No Parent Age	No Year of Swap	PSM Common Support	RI P-values
Panel A: GPA, Gr 8-10							
Leniency SD	-0.022***	-0.023***	-0.022***	-0.024***	-0.023***	-0.022***	-0.022***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Panel B: GPA, Gr 11-13							
Leniency SD	-0.020***	-0.021***	-0.021***	-0.021***	-0.021***	-0.021***	-0.020***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Panel C: Academic Track							
Leniency SD	-0.002	-0.002	-0.002	-0.002	-0.002	-0.003	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Panel D: HS Grad							
Leniency SD	-0.012***	-0.012***	-0.012***	-0.013***	-0.012***	-0.011***	-0.012***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Panel E: Start College							
Leniency SD	-0.011***	-0.011***	-0.011***	-0.012***	-0.010***	-0.015***	-0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Panel F: Years of Ed							
Leniency SD	-0.049***	-0.050***	-0.048***	-0.051***	-0.050***	-0.046***	-0.049***
	(0.009)	(0.010)	(0.009)	(0.010)	(0.009)	(0.010)	(0.009)

Note: * p<0.05, ** p<0.01, *** p<0.001.
The table presents the OLS estimates of the effect of GP sick note leniency. Estimating equation: $w_{ijkt} = \beta x_j + \pi_k + \boldsymbol{\theta_{it}} + \varepsilon_{ijkt}$, where w_{ijkt} is the outcome at the top of the column, x_j is a standardized continuous measure of GP sick note leniency, π_k are previous GP FE, and $\boldsymbol{\theta_{it}}$ is a vector of controls (sick leave days the year before swap, patient age, and patient sex). Displayed estimates are the coefficient β, the effect of a 1 SD increase in GP sick note leniency.
Standard errors in parentheses clustered at GP level.

APPENDIX

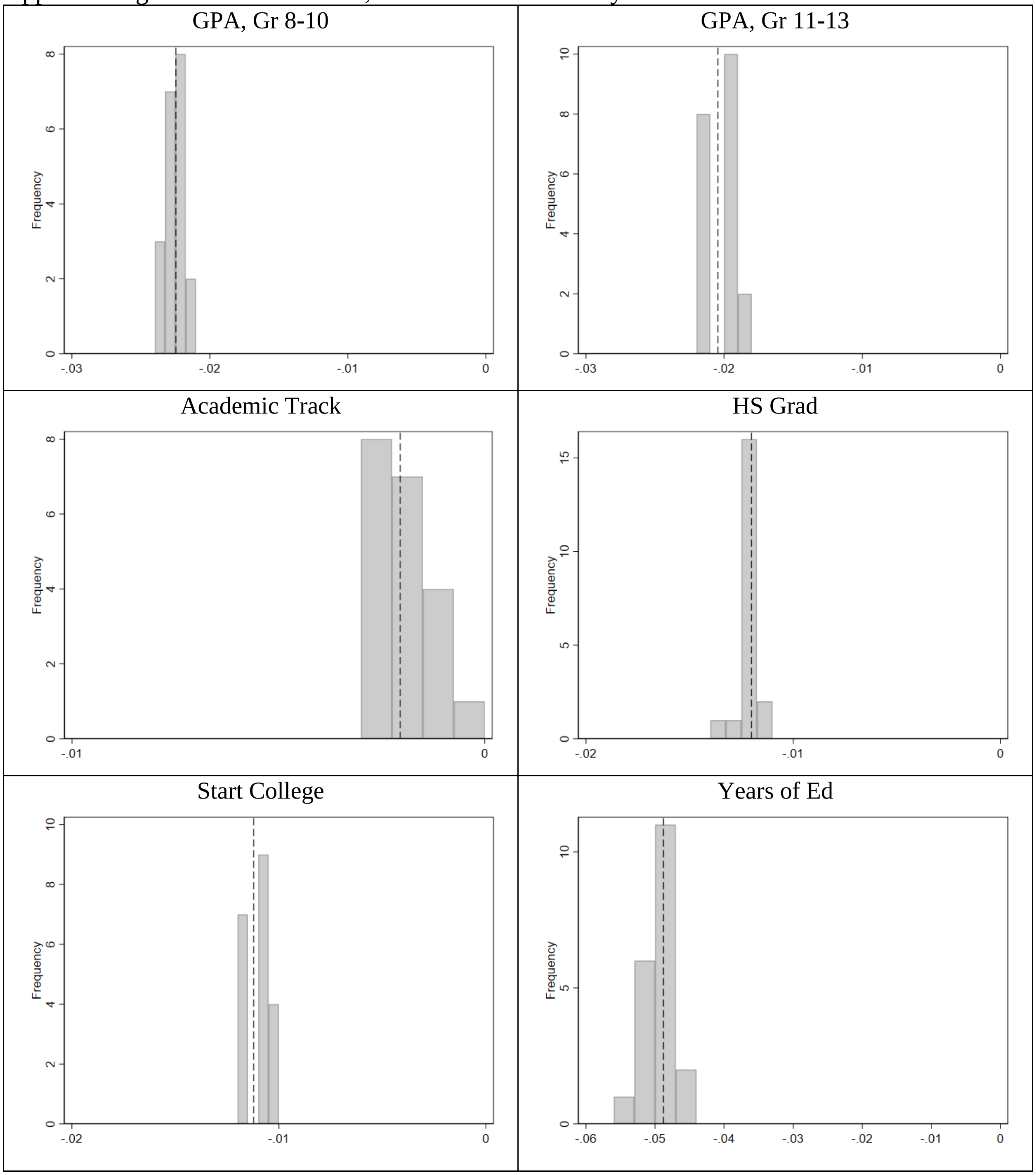
Appendix Figure A-1: Robustness, Leave Out One Year



Note: * p<0.05, ** p<0.01, *** p<0.001.

The figure presents the OLS estimates of the effect of GP sick note leniency, where each estimate omits one year of exogenous swaps. Estimating equation: $w_{ijkt} = \beta x_j + \pi_k + \boldsymbol{\theta_{it}} + \varepsilon_{ijkt}$, where w_{ijkt} is the outcome at the top of the column, x_j is a standardized continuous measure of GP sick note leniency, π_k are previous GP FE, and $\boldsymbol{\theta_{it}}$ is a vector of controls (sick leave days the year before swap, patient age, and patient sex). Displayed estimates are the coefficient β, the effect of a 1 SD increase in GP sick note leniency.

Appendix Figure A-2: Robustness, Leave Out One County



The figure presents the OLS estimates of the effect of GP sick note leniency, where each estimate omits one county of exogenous swaps. Estimating equation: $w_{ijkt} = \beta x_j + \pi_k + \boldsymbol{\theta_{it}} + \varepsilon_{ijkt}$, where w_{ijkt} is the outcome at the top of the column, x_j is a standardized continuous measure of GP sick note leniency, π_k are previous GP FE, and $\boldsymbol{\theta_{it}}$ is a vector of controls (sick leave days the year before swap, patient age, and patient sex). Displayed estimates are the coefficient β, the effect of a 1 SD increase in GP sick note leniency.

Appendix Table A-1: Effect on Own Mortality, 1 and 5 Years

	(1)	(2)
	1 Year Post Exposure	5 Year Post Exposure
Leniency SD	-0.000	-0.000
	(0.000)	(0.000)
Dep Mean	0.001	0.005
N	214,727	214,727

Note: * p<0.05, ** p<0.01, *** p<0.001.

The table presents the OLS estimates of the effect of GP sick note leniency. Estimating equation: $w_{ijkt} = \beta x_j + \pi_k + \boldsymbol{\theta_{it}} + \varepsilon_{ijkt}$, where w_{ijkt} is the outcome at the top of the column, x_j is a standardized continuous measure of GP sick note leniency, π_k are previous GP FE, and $\boldsymbol{\theta_{it}}$ is a vector of controls (sick leave days the year before swap, patient age, and patient sex). Displayed estimates are the coefficient β, the effect of a 1 SD increase in GP sick note leniency. Standard errors in parentheses clustered at GP level.

Appendix Table A-2: Effect on Childhood Educational Outcomes, by Early Childhood Ability (Grade 5 Standardized Exams)

High Ability

	(1)	(2)	(3)	(4)	(5)	(6)
	GPA, Gr 8-10	GPA, Gr 11-13	Academic Track	HS Grad	Start College	Years of Ed
Leniency SD	-0.011	-0.011	-0.007	-0.016*	-0.008	-0.065*
	(0.007)	(0.008)	(0.003)	(0.007)	(0.006)	(0.027)
Dep Mean	4.675	4.521	0.893	0.833	0.693	13.357
Dep SD	0.654	0.755	0.309	0.373	0.461	1.519
N	58,570	68,458	34,911	28,722	48,095	28,722

Low Ability

	(1)	(2)	(3)	(4)	(5)	(6)
	GPA, Gr 8-10	GPA, Gr 11-13	Academic Track	HS Grad	Start College	Years of Ed
Leniency SD	-0.014*	-0.021**	0.002	-0.010	-0.011*	-0.038
	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.023)
Dep Mean	3.967	3.912	0.737	0.656	0.446	12.635
Dep SD	0.727	0.793	0.440	0.475	0.497	1.914
N	91,915	104,468	43,476	45,418	72,819	45,418

Note: * p<0.05, ** p<0.01, *** p<0.001.
The table presents the OLS estimates of the effect of GP sick note leniency. Estimating equation: $w_{ijkt} = \beta x_j + \pi_k + \boldsymbol{\theta}_{it} + \varepsilon_{ijkt}$, where w_{ijkt} is the outcome at the top of the column, x_j is a standardized continuous measure of GP sick note leniency, π_k are previous GP FE, and $\boldsymbol{\theta}_{it}$ is a vector of controls (sick leave days the year before swap, patient age, and patient sex). Displayed estimates are the coefficient β, the effect of a 1 SD increase in GP sick note leniency.
Standard errors in parentheses clustered at GP level.

Appendix Table A-3: Effect on Childhood Educational Outcomes, by Parent Education

High Parent Education

	(1)	(2)	(3)	(4)	(5)	(6)
	GPA, Gr 8-10	GPA, Gr 11-13	Academic Track	HS Grad	Start College	Years of Ed
Leniency SD	-0.023***	-0.021***	-0.003	-0.010***	-0.012***	-0.039***
	(0.005)	(0.004)	(0.002)	(0.003)	(0.002)	(0.011)
Dep Mean	4.266	4.092	0.778	0.707	0.654	12.847
Dep SD	0.783	0.850	0.416	0.455	0.476	1.841
N	229,024	329,786	191,640	224,185	310,187	224,185

Low Parent Education

	(1)	(2)	(3)	(4)	(5)	(6)
	GPA, Gr 8-10	GPA, Gr 11-13	Academic Track	HS Grad	Start College	Years of Ed
Leniency SD	-0.017*	-0.015*	0.004	-0.014***	-0.008**	-0.059***
	(0.007)	(0.006)	(0.005)	(0.004)	(0.003)	(0.016)
Dep Mean	3.793	3.728	0.638	0.531	0.528	12.131
Dep SD	0.812	0.879	0.481	0.499	0.499	2.013
N	80,754	125,887	63,160	96,088	138,007	96,088

Note: * $p<0.05$, ** $p<0.01$, *** $p<0.001$.
The table presents the OLS estimates of the effect of GP sick note leniency. Estimating equation: $w_{ijkt} = \beta x_j + \pi_k + \boldsymbol{\theta_{it}} + \varepsilon_{ijkt}$, where w_{ijkt} is the outcome at the top of the column, x_j is a standardized continuous measure of GP sick note leniency, π_k are previous GP FE, and $\boldsymbol{\theta_{it}}$ is a vector of controls (sick leave days the year before swap, patient age, and patient sex). Displayed estimates are the coefficient β, the effect of a 1 SD increase in GP sick note leniency.
Standard errors in parentheses clustered at GP level.

Appendix Table A-4: Effect on Childhood Educational Outcomes, by Parent Income

High Parent Income

	(1)	(2)	(3)	(4)	(5)	(6)
	GPA, Gr 8-10	GPA, Gr 11-13	Academic Track	HS Grad	Start College	Years of Ed
Leniency SD	-0.028***	-0.018***	-0.006	-0.009**	-0.015***	-0.035*
	(0.006)	(0.005)	(0.003)	(0.003)	(0.003)	(0.014)
Dep Mean	4.271	4.081	0.778	0.707	0.644	12.847
Dep SD	0.787	0.856	0.416	0.455	0.479	1.841
N	149,906	233,999	138,174	159,048	220,098	159,048

Low Parent Income

	(1)	(2)	(3)	(4)	(5)	(6)
	GPA, Gr 8-10	GPA, Gr 11-13	Academic Track	HS Grad	Start College	Years of Ed
Leniency SD	-0.019***	-0.021***	0.002	-0.013***	-0.008***	-0.054***
	(0.005)	(0.005)	(0.003)	(0.003)	(0.002)	(0.012)
Dep Mean	4.017	3.892	0.702	0.600	0.585	12.410
Dep SD	0.829	0.883	0.457	0.490	0.493	1.979
N	162,086	224,723	117,621	163,019	230,697	163,019

Note: * p<0.05, ** p<0.01, *** p<0.001.
The table presents the OLS estimates of the effect of GP sick note leniency. Estimating equation: $w_{ijkt} = \beta x_j + \pi_k + \boldsymbol{\theta_{it}} + \varepsilon_{ijkt}$, where w_{ijkt} is the outcome at the top of the column, x_j is a standardized continuous measure of GP sick note leniency, π_k are previous GP FE, and $\boldsymbol{\theta_{it}}$ is a vector of controls (sick leave days the year before swap, patient age, and patient sex). Displayed estimates are the coefficient β, the effect of a 1 SD increase in GP sick note leniency.
Standard errors in parentheses clustered at GP level.

Appendix Table A-5: Effect on Childhood Educational Outcomes, by Parent Public Employee

Public Employee

	(1)	(2)	(3)	(4)	(5)	(6)
	GPA, Gr 8-10	GPA, Gr 11-13	Academic Track	HS Grad	Start College	Years of Ed
Leniency SD	-0.029***	-0.032***	-0.001	-0.012**	-0.012***	-0.046**
	(0.007)	(0.007)	(0.004)	(0.004)	(0.003)	(0.017)
Dep Mean	4.197	4.019	0.762	0.676	0.648	12.720
Dep SD	0.810	0.869	0.426	0.468	0.478	1.890
N	80,435	118,450	68,885	84,411	117,444	84,411

Not Public Employee

	(1)	(2)	(3)	(4)	(5)	(6)
	GPA, Gr 8-10	GPA, Gr 11-13	Academic Track	HS Grad	Start College	Years of Ed
Leniency SD	-0.016**	-0.012*	-0.001	-0.011***	-0.009***	-0.046***
	(0.006)	(0.005)	(0.003)	(0.003)	(0.003)	(0.013)
Dep Mean	4.132	3.983	0.733	0.653	0.620	12.626
Dep SD	0.816	0.870	0.442	0.476	0.485	1.924
N	173,392	238,787	138,320	177,129	240,084	177,129

Note: * p<0.05, ** p<0.01, *** p<0.001.
The table presents the OLS estimates of the effect of GP sick note leniency. Estimating equation: $w_{ijkt} = \beta x_j + \pi_k + \boldsymbol{\theta_{it}} + \varepsilon_{ijkt}$, where w_{ijkt} is the outcome at the top of the column, x_j is a standardized continuous measure of GP sick note leniency, π_k are previous GP FE, and $\boldsymbol{\theta_{it}}$ is a vector of controls (sick leave days the year before swap, patient age, and patient sex). Displayed estimates are the coefficient β, the effect of a 1 SD increase in GP sick note leniency.
Standard errors in parentheses clustered at GP level.

Appendix Table A-6: Distribution of Leniency by Sick Leave Reason

ICPC	Leniency Standard Deviation
A General and unspecified	2.572
B Blood, blood forming organs, lymphatics, spleen	0.917
D Digestive	2.130
F Eye	0.717
H Ear	0.763
K Circulatory	1.838
L Musculoskeletal	6.802
N Neurological	2.754
P Psychological	5.368
R Respiratory	1.390
S Skin	1.023
T Endocrine, metabolic and nutritional	1.224
U Urology	0.537
W Pregnancy, childbirth, family planning	2.671
X Female genital system and breast	1.349
Y Male genital system	0.497
Z Social problems	0.049

Note: Categories are based on the International Classification of Primary Care, 2nd edition.

Appendix Table A-7: Correlates of GP Sick Leave Leniency

	(1)	(2)	(3)	(4)	(5)	(6)
	GP Quality	GP List Length	GP Max List Len.	GP Full List	Patient Per GP (Muni)	High Pt Per GP (Muni)
Leniency SD	-0.033	-0.683	-1.390	-0.004	-0.098	-0.004
	(0.019)	(3.178)	(2.923)	(0.004)	(3.022)	(0.004)
Dep Mean	0.004	1083.576	1197.259	0.360	1102.032	0.570
Dep SD	0.991	375.769	353.931	0.444	353.437	0.492
N	1,976	5,551	5,551	5,551	5,551	5,551

Note: * p<0.05, ** p<0.01, *** p<0.001.
The table presents the OLS estimates of the correlates of GP sick note leniency from bivariate regression of the characteristics at the top of the column on the standardized leniency measure. Displayed estimates are the coefficient of a 1 SD increase in GP sick note leniency. Robust standard errors in parentheses.

Appendix Table A-8: Sick Leave Leniency and Health Care Utilization

Panel A: 1 Year Post Exposure			
	(1)	(2)	(3)
	Check-ups, Chronic Cond.	ER Visits	Inpatient Days
Leniency SD	-0.002	0.005	-0.008
	(0.014)	(0.004)	(0.009)
Dep Mean	0.217	0.251	0.126
N	30635	158730	158730

Panel B: 5 Year Post Exposure			
	(1)	(2)	(3)
	Check-ups, Chronic Cond.	ER Visits	Inpatient Days
Leniency SD	0.003	0.005	0.008
	(0.005)	(0.006)	(0.006)
Dep Mean	0.074	0.293	0.164
N	47147	123901	123901

Note: * p<0.05, ** p<0.01, *** p<0.001.

The table presents the OLS estimates of the effect of GP sick note leniency. Estimating equation: $w_{ijkt} = \beta x_j + \pi_k + \boldsymbol{\theta_{it}} + \varepsilon_{ijkt}$, where w_{ijkt} is the outcome at the top of the column, x_j is a standardized continuous measure of GP sick note leniency, π_k are previous GP FE, and $\boldsymbol{\theta_{it}}$ is a vector of controls (sick leave days the year before swap, patient age, and patient sex). Displayed estimates are the coefficient β, the effect of a 1 SD increase in GP sick note leniency.

Standard errors in parentheses clustered at GP level.