Avoiding the Risk, Bearing the Cost: Evidence from General Health Screening in Korea during the COVID-19 Pandemic*

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Abstract

This study examines the unintended health consequences of voluntary responses to COVID-19. We focus on general health screening in Korea, using administrative data that link medical claims and screening records. At the national level, screening rates declined markedly in 2020, the first year of the pandemic, relative to counterfactual trends. Complementing this aggregate pattern, individual-level analysis reveals notable heterogeneity: declines were larger among those with higher predicted risk of chronic disease. We then assess the consequences of forgone screening, employing propensity score matching and event study designs. Our estimates show that, had they been screened, individuals who missed screening would have been more likely to initiate care for chronic diseases. The costs of missed screening were especially large among those at higher predicted risk of chronic disease. Such delays in management led to more advanced conditions at the time of care initiation. Our findings show that, even without strict quarantine policies, voluntary responses to infection can undermine preventive care, disproportionately affecting high-benefit groups. This underscores the importance of balancing infection control with the continuity of preventive care during health crises.

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1 Introduction

During the COVID-19 pandemic, individuals voluntarily adopted preventive behaviors—such as mask-wearing and avoiding public spaces—in response to infection risk (Gupta et al., 2020). This reflects what is often referred to as a prevalence response, a specific type of voluntary response to rising infection risk (Philipson, 2000). Notably, recent evidence suggests that government-imposed interventions (e.g., lockdowns) played a relatively limited role, whereas these voluntary responses accounted for much of the observed reduction in infection rates (Agrawal et al., 2023; Cantor et al., 2022; Ziedan et al., 2020).

While these voluntary responses were crucial in curbing the spread of COVID-19, they may have also led to unintended harms. For example, the avoidance of healthcare facilities is likely to have disrupted routine and preventive care, such as health screening and chronic disease management, potentially worsening health outcomes for vulnerable populations (Bennett et al., 2015). These concerns highlight the need for a clearer understanding of the unintended health consequences associated with voluntary responses, as such knowledge could help inform public health policies that better balance infection control with the mitigation of collateral harms. Yet empirical evidence on these consequences remains limited (Dorn et al., 2023).

However, identifying the health impact of voluntary responses during the pandemic presents important empirical challenges. First, it is difficult to disentangle these individual-level decisions from the effects of public health interventions. In many countries, declines in non-COVID health care utilization occurred alongside government-imposed mobility restrictions. In addition, infection control policies—such as the temporary closure of facilities following confirmed patient visits—may have reduced the supply of non-COVID care. Second, even in the absence of such interventions, other pandemic-related factors—such as actual infection or income shocks—may have influenced health care demand, complicating efforts to isolate the effect of voluntary responses alone.

In this regard, the Korean government's response to the pandemic and the context of the general health screening program offer a suitable setting for analyzing the health impact of voluntary responses. Unlike other high-income countries, Korea did not implement lockdowns in 2020 (Ari-

adne Labs, 2025). Its healthcare system remained relatively stable, partly due to the low number of confirmed cases—about 1,200 per 1 million people by the end of the year, well below the global average (Mathieu et al., 2020). Only a small number of healthcare facilities experienced temporary closures. These conditions minimize confounding from policy-induced constraints, enabling a clearer identification of the effect of voluntary responses on health screening take-up. At the same time, the general health screening program is designed to cover the entire population and imposes no out-of-pocket costs (Kang, 2022). As a result, economic barriers to screening take-up are minimized, reducing potential confounding from income shocks.

We use administrative data from the National Health Insurance Service (NHIS), which administers the program as Korea's single insurer and maintains detailed records linking medical claims with health screenings. This allows us to examine heterogeneity in individuals' responses to COVID-19 based on their health status, and to quantify the health consequences of missed screenings.

To examine the effect of COVID-19 on health screening participation, we conduct both a national-level and an individual-level analysis. At the national level, we apply a modified interrupted time series approach that estimates the counterfactual trend in weekly screening rates absent the pandemic, using 2017–2019 data. We then compare this counterfactual with the actual screening rates observed in 2020 and 2021. Complementing this, the individual-level analysis investigates whether responses to COVID-19 varied according to individuals' risk of chronic disease. This heterogeneity is noteworthy because high-risk individuals may benefit more from timely screening, yet hypertension and diabetes—the main target diseases—are also major risk factors for severe COVID-19. Thus, it is ex ante unclear whether high-risk groups would reduce screening relative to lower-risk groups, making this an empirical question. To answer this question, we focus on individuals who had not used health care for hypertension or diabetes in the past three years but had received a health screening one to two years earlier. We then predict their risk of chronic disease using prior screening records and claims data.

According to the national-level analysis, health screening rates dropped sharply during the

initial COVID-19 outbreak in early 2020, followed by a gradual recovery consistent with a pattern of intertemporal substitution. Over the course of 2020, screening rates declined by approximately 7.520 percentage points relative to the counterfactual (Figure 1(a)). In contrast, despite a higher number of confirmed cases in 2021, screening rates largely aligned with the counterfactual trend (Figure 1(b)). This suggests that the decline in screening was largely confined to the first year of the pandemic. When accounting for the extension of the screening period, the decline was partially offset, yet a cumulative decrease of about 5.680 percentage points remained in 2020 (Figure 2).

Next, the individual-level analysis shows that individuals with higher chronic disease risk had a greater decline in the probability of receiving a health screening during the pandemic. Based on hypertension risk, the lowest-risk group (1st quintile) experienced a 4.38 percentage point decline in screening, while the highest-risk group (5th quintile) showed an additional 2.30 percentage point drop (Figure 3(a)). A similar but smaller pattern is observed for diabetes risk (Figure 3(b)). We further break down the predicted risk into its individual predictors and examine how screening uptake varied across these factors. In particular, participation declined most notably among older adults, medical aid recipients, and individuals with elevated biomarkers—such as high BMI, fasting blood glucose, and blood pressure. These findings suggest that high-risk individuals were less likely to receive screening during the pandemic, likely due to voluntary responses in the absence of strict containment measures.

To assess the health consequences of reduced screening in 2020, we estimate the Average Treatment Effect on the Untreated (ATU) using propensity score matching. The same variables as in the risk prediction models are employed to account for differences in health status and prior utilization. Although this approach balances observed characteristics, concerns about selection remain, particularly if unobserved risk perceptions influenced screening decisions. The matching covariates are plausibly tied to risk perception during the pandemic—for example, individuals at higher risk of chronic disease were also recognized as high-risk groups for COVID-19 (Centers for Disease Control and Prevention, 2025; Geng et al., 2021). Yet actual and perceived risks are not perfectly aligned, and other sources of unobserved heterogeneity may remain. To assess the

potential for systematic bias, we also implement an event study that evaluates whether screened and unscreened individuals exhibited similar care patterns prior to screening and whether screening subsequently triggered distinct changes.

The ATU estimates indicate that, among the untreated, receiving a screening would have increased the probability of initiating hypertension-related care by 2.58 percentage points, equivalent to roughly 35% of the untreated group's mean (Table 2). Similarly, the number of related care visits would have increased by 0.217, corresponding to about 46% of the mean. For diabetes, the probability of initiating care would have increased by 2.42 percentage points, while the number of related visits would have increased by 0.098—representing 35% and 41% of the mean, respectively. These findings indicate that delays in health screening during the COVID-19 pandemic hindered the timely management of chronic diseases.

According to the event study results, the likelihood of initiating care and the frequency of related visits both rise sharply after screening. For hypertension, the probability of care initiation increases by 1.140 percentage points, and the number of visits remains elevated thereafter (Figure 6(a), 6(b)). A similar pattern emerges for diabetes (Figure 6(c), 6(d)). By contrast, no changes appear in the placebo group assigned a pseudo screening month. In sum, these results reinforce a causal interpretation of the ATU estimates from propensity score matching. They further show that missed screenings hampered not only the initiation of chronic disease care but also its subsequent management.

Having established that missed screenings delay care for chronic diseases, we next quantify the downstream impact of such delays. This allows us to offer more context on the welfare implications—specifically, whether short-term avoidance of preventive care during the pandemic led to clinically meaningful deterioration in health. Our analysis focuses on the presence of complications associated with hypertension and diabetes at the time of care initiation. We find that health screening substantially reduces the likelihood of initiating care with complications. For hypertension, the probability declines by 5.7 percentage points—about 20 percent relative to the mean of the untreated group. For diabetes, the corresponding reduction is 2.9 percentage points, or 13 percent

(Table 3).

The rest of the paper is organized as follows. Section 2 reviews the related literature and provides background for our study. Section 3 describes the data. Section 4 analyzes changes in screening rates during the COVID-19 pandemic, and Section 5 examines the effects of health screenings on chronic disease management. Section 6 concludes.

2 Background

2.1 Related Literature

The COVID-19 pandemic produced not only direct health burdens but also indirect ones arising from delayed or forgone care for non-COVID conditions (Dorn et al., 2023). In the United States, Whaley et al. (2020) show that overall health care use fell by 23% in March 2020 among privately insured individuals, with substantial declines in preventive and elective care. McBain et al. (2021) report that mammography and colonoscopy rates declined by more than 90% immediately after the national emergency declaration, though screening rebounded within months as health systems adapted. A similar pattern is documented by Danagoulian and Wilk (2022) in the context of dental care. At the same time, the sharp increase in telemedicine uptake partly offset the decline in in-person visits during the pandemic: Whaley et al. (2020) report that virtual visits replaced roughly 40% of lost office visits in the U.S., and Busso et al. (2022) find a 230% rise in consultations in Argentina. Yet these shifts only partially compensated for the disruption, leaving many health care needs unmet.

A substantial portion of the decline reflects involuntary disruptions stemming from government policies. Studies exploiting geographic and temporal variation in these measures have quantified their effects. Ziedan et al. (2020) estimate that state-mandated closures account for roughly one-third of the approximately 40% nationwide drop in outpatient visits observed in the early months of the U.S. pandemic. Similarly, Cantor et al. (2022) find that county-level shelter-in-place orders significantly reduced preventive and elective service utilization. Ziedan et al. (2022) take a different

approach, exploiting variation across appointment cohorts in their exposure to cancellation risk following the emergency declaration, and document large-scale disruptions to scheduled care.

Beyond such involuntary disruptions, the economic epidemiology literature suggests that individuals may voluntarily adjust their behaviors in response to infection risk. Philipson (2000) theoretically shows that rising prevalence of infectious disease can induce preventive behaviors that help limit spread, and empirical evidence confirms such prevalence responses: local pertussis outbreaks increased vaccination uptake (Oster, 2018a; Schaller et al., 2019), while the H1N1 pandemic improved hygiene practices with unintended health benefits (Agüero & Beleche, 2017; Hong et al., 2022). However, the potential downsides of these individual choices have received far less attention. This is particularly relevant because the trade-off between infection risk and untreated conditions varies with health status, rendering the overall welfare effect uncertain.

Our study makes three contributions to the literature. First, we document voluntary disruptions of care during the pandemic and demonstrate their downstream health consequences for chronic disease management. A close comparison with Ziedan et al. (2022) shows how our study builds on prior work. Whereas they analyze how the health care system prioritized services during the crisis, we examine the ways in which individuals prioritized their own health needs. This focus complements existing evidence: while policy-driven shocks typically fade once restrictions are lifted, voluntary avoidance stems from individual perceptions of risk and thus calls for different policy responses.

Second, we examine heterogeneity by underlying health status. The motivation is the trade-off that the same conditions making preventive care most valuable—such as chronic disease risk—also heighten vulnerability to infection during the pandemic. As emphasized by Chandra and Skinner (2012), the welfare impact of changes in care utilization depends on whether foregone care is high-value or low-value. Our analysis speaks directly to this distinction, showing that high-risk patients—whose screenings are most likely to be high-value—were disproportionately more likely to forgo them.

Finally, we provide more granular evidence on the health burden of the pandemic. As Chen

and McGeorge (2020) argue, assessing the health consequences of pandemics requires attention to intermediate outcomes that shape longer-term mortality. Yet early research has focused primarily on excess mortality (Laliotis et al., 2023; Zhang, 2021). We document an important channel through which disrupted health care translates into long-term health consequences, focusing on delays in the management of chronic conditions.

2.2 National Health Screening Program in Korea

The national health screening program in Korea consists of four major components, classified by target age group and purpose. These include, first, general health screenings and cancer screenings for adults; second, health screenings for adolescents; and third, screenings for infants and young children. This study focuses on the general health screening, which serves as a primary route for diagnosing chronic conditions such as hypertension and diabetes.[1]

Since its introduction in 1980 for government employees and private school staff, Korea's national health screening program has gradually expanded its target population. This expansion aimed to maximize participation rates and applies to the general health screening as well (Kang, 2022). All costs are fully covered by the NHIS, and eligible individuals can choose any time within the year to receive the screening. The number of screening institutions increased steadily from 16,411 in 2011 to 23,030 in 2019 (National Assembly Budget Office, 2021), contributing to improved accessibility and minimizing supply-side constraints. As of 2020, regional subscribers (i.e., self-employed and non-employed individuals) are eligible for screening once every two years if they are household heads or household members aged 20 or older. Among employee insured individuals, non-office workers undergo screening annually, while office workers are screened once every two years (National Health Insurance Service, 2021). Dependents of employee insured individuals are also eligible for screening once every two years if they are aged 20 or older.

[1] According to the 2019 Korea National Health and Nutrition Examination Survey (KNHANES) (Korea Disease Control and Prevention Agency, 2025), among the 72.7% of respondents aged 40 to 79 (n=4,270) who reported receiving a health screening within the past two years (excluding cancer screenings), 90.8% received the general health screening provided by the NHIS, while only 6.9% received a comprehensive screening paid out-of-pocket.

The institutional characteristics of the general health screening program offer a suitable context for analyzing the effects of voluntary responses to COVID-19. First, the program is characterized by no out-of-pocket cost and easy accessibility, which implies that individuals' decisions to receive screening are more likely to be influenced by infection risk during the pandemic. Second, the NHIS, which administers the general health screening program as the single insurer in Korea, maintains an integrated database that links individuals' health screening records with their medical claim data. This data integration provides several empirical advantages. It enables the prediction of chronic disease risk based on rich health indicators and personal characteristics, allowing for the analysis of heterogeneous responses to the pandemic. Furthermore, by tracking changes in individuals' health care utilization following screenings, the potential costs of forgone screenings can be estimated.

During the study period, two notable institutional changes occurred. First, in 2019, the eligible age for dependents of regional subscribers was lowered from 40 to 20, significantly altering the composition of the eligible population under the age of 40. This makes it difficult to compare their screening rates before and after the pandemic. Accordingly, individuals under the age of 40 were excluded from the analysis. Second, due to the COVID-19 pandemic, the screening period was temporarily extended to the end of June in the following year. The extension was intended to reduce infection risk by easing the year-end surge in examinees. As a result, focusing on screening uptake within the standard one-year period may lead to an overestimation of the effect of the pandemic. A more detailed discussion of this issue is provided in Section 4.

2.3 COVID-19 in Korea and Government Response

The COVID-19 conditions in Korea and the government's response during the first year of the pandemic provide a suitable context for understanding the health consequences of individuals' voluntary responses to infection risk.

The low infection rate in the first year of the pandemic limits the possibility that either COVID-19 infection itself or constraints on health care provision significantly affected screening rates. Korea experienced three major waves of infection during 2020 (Y. Kim et al., 2021). The first wave

occurred following the country's first confirmed case on January 20, 2020, with approximately 10,774 confirmed cases concentrated in two regions—Daegu and Gyeongsangbuk-do. The second wave emerged around August, centered on religious facilities and mass gatherings in the Seoul metropolitan area. The third wave, which began at the end of the year, was larger in scale than the previous two and spread nationwide. Despite these waves, as of the end of December 2020, Korea's cumulative number of confirmed cases was approximately 1,208 per one million population—substantially lower than the global average of 12,720 (Mathieu et al., 2020). In addition, Korea continued to provide non-COVID health care during the pandemic, supported by its ample health care capacity (Her, 2020; Oh et al., 2020).

Next, the Korean government's approach to managing COVID-19 also constitutes a critical contextual aspect. Throughout 2020, Korea did not implement strict containment measures such as stay-at-home orders, which were widely adopted in other high-income countries (Ariadne Labs, 2025). Instead, the government focused on large-scale diagnostic testing and contact tracing of confirmed cases, encouraging voluntary preventive behavior by sharing such information through regular public briefings (Her, 2020). Consistent with this strategy, social distancing, which began on February 29, 2020, was also implemented in the form of a public campaign. At the peak of the first wave, additional measures were introduced, including the temporary closure of multi-use facilities and public institutions. While the stringency of containment policies was adjusted several times depending on the spread of COVID-19, no nationwide mobility restrictions or limitations on access to health care facilities were imposed. In particular, although social distancing was applied to multi-use facilities, it did not include health care facilities, making it likely that the provision of health screening was not restricted.[2]

[2]In some instances, health care facilities temporarily closed following visits by COVID-19 patients. However, such closures are unlikely to have significantly affected the overall supply of health care. According to data from loss compensation applications submitted by health care facilities in 2020, only about 1.7% of facilities were officially closed, suspended, or ordered to disinfect due to confirmed case exposure (Central Disaster and Safety Countermeasures Headquarters, 2020a, 2020b, 2020c, 2020d, 2020e). If the degree of disruption were sufficient to restrict health care supply, we would expect to observe a subsequent increase in unmet care needs resulting from supply-side constraints. To examine this possibility, we refer to responses from the KNHANES regarding the incidence and reasons for unmet care needs (Appendix Figure A1). Notably, the proportion of individuals reporting unmet care needs slightly declined, from 0.076 before the pandemic to 0.062 during the pandemic. Nevertheless, among the reasons reported, there was a clear rise in cases attributed to fear of infection.

3 Data

This study utilizes the National Health Information Database from the NHIS (National Health Insurance Service, 2025). Based on this database, researchers can flexibly define the study population, determine the appropriate sample size, and specify the sampling period using the entire population of health insurance enrollees in Korea. The dataset used in this study consists of health insurance enrollees who were 20 years of age or older as of 2019, selected through random sampling stratified by sex and age.[3] It includes enrollee information such as sex, age, insurance type, and insurance premium, as well as medical claims data. For individuals who received a health screening, the dataset additionally contains biomarkers and self-reported survey information, such as health behaviors.

We impose two common restrictions on our study sample. First, we limit the sample to individuals who are at least 40 years old and younger than 80. This restriction reflects the fact that, prior to 2019, individuals under the age of 40 were generally not eligible for health screenings, except those covered by employee insurance. Second, we exclude all observations in which the individual received a health screening even though they were not eligible.

For each analysis, we apply additional restrictions depending on its specific purpose. These are summarized in Table 1. In Section 4, we aggregate samples from 2016 to 2021 to the weekly level for the national-level analysis. In the individual-level analysis, which examines heterogeneous responses to COVID-19, we use a sample of individuals who had not used health care for hypertension and diabetes in the past three years and had received a health screening within the past one to two years. We use a dummy variable indicating whether an individual received a health screening as the outcome variable. In Section 5, we use samples from 2020 and 2021 to examine the effects of delayed health screening on health care utilization. To this end, we construct separate outcome variables for hypertension and diabetes, including initiation of care and the number of related care visits for each condition.[4] We additionally examine whether the reduction in health screenings led

[3]The dataset includes 1,448,121 unique individuals as of 2019.

[4]Health care utilization related to hypertension and diabetes is identified using diagnosis codes I10–I13 for hypertension and E10–E14 for diabetes, based on the 7th revision of the Korean Standard Classification of Diseases (KCD-7).

to the initiation of care at more severe stages of chronic disease, by including, for each condition, outcome variables indicating the presence of complications.[5]

4 Changes in Health Screening Rates During the COVID-19 Pandemic

4.1 Empirical Approach

4.1.1 National-Level Changes in Health Screening Rates

Eligible individuals are allowed to choose when to receive screening within the designated screening period. As a result, concerns about COVID-19 infection may have led them to respond in two distinct ways regarding the timing of screening. First, they may have avoided periods of high infection risk or heightened uncertainty and instead chosen to receive screening during safer periods, which may reflect intertemporal substitution. Second, they may have chosen not to receive a screening at all during the year. Accordingly, we conduct an analysis at the weekly level to examine both types of responses.

In order to assess changes in health screening rates during the COVID-19 pandemic, we employ a modified interrupted time series approach. Specifically, we estimate the counterfactual trend in screening rates that would have been observed in the absence of the pandemic. To this end, we use data from 2017 to 2019 and estimate the following equation:[6]

$$Y_{wt} = \beta_0 + \beta_1 Year_t + \beta_2 Holiday_{wt} + \delta_w + \epsilon_{wt} \tag{1}$$

where the outcome variable (Y_{wt}) is the number of health screenings per 100 eligible individuals

[5]For hypertension, complications include coronary artery disease (I20–I25), cerebrovascular disease (I60–I69), heart failure (I50), and chronic kidney disease (N18, N19) (National Health Insurance Service, 2023). For diabetes, subcategories of E10–E14 that indicate diabetes with complications are included.

[6]The results are robust to the choice of sample period used to estimate the counterfactual trend, as estimates based on equation 1, using samples from 2015–2019, 2016–2019, and 2017–2019, yield consistent results, which are available upon request.

in week w and year t. To account for time trends in screening rates, we include a yearly linear trend ($Year_t$) in the model (Appendix Figure A2). The number of holidays ($Holiday_{wt}$) is added to control for holiday effects.[7] Since screening rates tend to be lower at the beginning of the year and increase toward the end, we include week fixed effects (δ_w) to account for seasonality. Standard errors are robust to heteroskedasticity.

Using the estimates from equation 1, we calculate counterfactuals for 2020 and 2021. The difference between the observed and counterfactual screening rates can be interpreted as the effect of the pandemic on screening. For this interpretation to be valid, we assume that, in the absence of the pandemic, health screening in 2020 and 2021 would have followed a trend similar to the counterfactual. To support this assumption, we conduct falsification tests using samples from the pre-pandemic period.

As noted in Section 2.3, the health screening period was extended at the end of 2020. If the effects of this extension are not taken into account, the decline in screening rates attributed to the pandemic may be overestimated. Specifically, because screenings are typically concentrated toward the end of the year, the extension may have allowed individuals to avoid the heightened infection risk during that period. If individuals instead received screening during the extended period, the decline observed during the regular screening period would overstate the true reduction. Therefore, we estimate the change in screening rates from 2020 to 2021 relative to the counterfactual screening rates for individuals eligible in 2020. To do this, we estimate equation 1 for years t and June $t+1$, using the number of individuals screened relative to those eligible in each cohort as the outcome variable. To avoid contamination from the pandemic period in year $t+1$ of the 2019 cohort, we use the 2016–2018 sample instead.

[7] We considered alternative functional forms for holidays, including a dummy variable for the presence of any holiday and categorical dummies based on the number of holidays. Among these, we selected the continuous variable for the number of holidays, as it yielded the lowest root mean squared error in the counterfactual estimation model.

4.1.2 Heterogeneous Responses by Chronic Disease Risk

Chronic disease risk is closely related to both the expected benefits and the costs of undergoing screening during the pandemic. On the one hand, individuals at higher risk for chronic disease may benefit more from screening, as it enables earlier detection and management of their conditions. On the other hand, the health costs of COVID-19 infection are particularly high for these individuals. For example, those with chronic diseases are known to experience more severe infections and face a higher risk of death (Centers for Disease Control and Prevention, 2025; Geng et al., 2021). Therefore, it is ex ante unclear whether high-risk individuals would reduce or maintain screening uptake during the pandemic, making this an empirical question.

To examine heterogeneity in response to COVID-19, we restrict the sample to individuals with no health care utilization related to hypertension and diabetes in the past three years. In addition, we further restrict the sample to individuals who received a health screening within the past one to two years, for two main reasons. First, biomarkers such as blood pressure and blood glucose are crucial for predicting chronic disease risk, and this information is only available for individuals who have received a health screening. Second, excluding individuals who had not received a screening in recent years helps ensure that any observed change in screening uptake during the pandemic reflects a response to COVID-19 risk, rather than pre-existing non-participation. The individual-level analysis uses the following equation:

$$Y_{it} = \beta_0 + \sum_{j=2}^{5} \beta_1^j 1[RiskQ_{it} = j] \times COVID_t + \beta_2 COVID_t + \beta_3 Year_t + \gamma' X_{it} + \epsilon_{it} \qquad (2)$$

where the outcome variable is an indicator that equals 1 if individual i received a screening in year t through June of $t+1$, and 0 otherwise. $1[RiskQ_{it} = j]$ takes the value 1 if the predicted risk quintile for hypertension or diabetes is j. A detailed description of the risk prediction is provided in Appendix A.[8] The variable of interest, $COVID$, is a dummy variable that equals 1 if the individual

[8]We estimate logistic regression models to predict the risk of developing hypertension and diabetes. The sample consists of individuals aged 40 to 79 in 2015 who have no prior health care utilization related to these conditions in the preceding three years and have received a health screening within the past one to two years. To mitigate overfitting, we employ 5-fold cross-validation during model training. Model performance is evaluated using AUC values from

was eligible for screening in 2020, and 0 if they were eligible between 2016 and 2018. A linear year trend ($Year_t$) is also included. The model controls for individual characteristics (X_{it}) to account for changes in health status and age due to the panel structure of the data, as well as changes in sample composition. The control variables consist of dummy variables for predicted risk quintiles, demographic characteristics, and screening-related variables (e.g., biomarkers, health behaviors, family history of chronic disease) from previous screenings, as well as Elixhauser comorbidity conditions. More details on the control variables are provided in Table A1. Standard errors are robust to heteroskedasticity.

4.2 Changes in Health Screening Rates

4.2.1 Baseline Results

Figure 1 presents the weekly changes in health screening rates from the counterfactual, calculated using equation 1. Figure 1(a) shows that the decline in screening rates began around the time when the first confirmed case of COVID-19 was reported in Korea. During the initial wave of the pandemic (up to week 14 of 2020—early April), screening rates exhibited a clear dip. The largest drop occurred at the peak of the outbreak, with screening rates falling by approximately 1 percentage point compared to the counterfactual. As the first wave subsided, the magnitude of the decline diminished. Nevertheless, a significantly negative change persisted through week 22 of 2020 (late May), with the cumulative decline reaching approximately 9.378 percentage points. In the weeks that followed, the screening rate exceeded the counterfactual. This pattern is consistent with intertemporal substitution, whereby individuals who postponed screenings during periods of heightened uncertainty received them later—when the perceived risk had decreased and the health care system had adapted. The recovery continued through week 47 of 2020 (in November), with the cumulative decline narrowing to 4.045 percentage points. However, toward the end of the year, screening rates declined again, as the number of confirmed cases surged beyond earlier waves and the government announced an extension of the screening period (week 44). By the end of 2020, the

out-of-sample predictions (Appendix Table A2).

overall screening rate had fallen by 7.520 percentage points.

Figure 1(b) shows that, unlike in 2020—when screening rates exhibited a clear pattern of decline and recovery corresponding to shifts in COVID-19 risk—changes in 2021 remained close to zero throughout the year. Despite the substantially higher number of confirmed cases in 2021 compared to 2020, the absence of marked deviation may reflect individuals' psychological adaptation to COVID-19 risk or pandemic fatigue, resulting in reduced behavioral elasticity in response to infection risk (Droste & Stock, 2021).[9] It may also reflect improvements in the management of COVID-19 risk through infrastructural adaptation (Ha & Kim, 2024). However, as in 2020, the government announced an extension of the screening period toward the end of 2021, after which screening rates declined once again. These results suggest that the impact of the pandemic on screening uptake was largely confined to 2020 and underscore the importance of accounting for the extended screening period in the analysis.[10]

4.2.2 Accounting for the Screening Period Extension

Section 4.2.1 shows that the extension of the screening period contributed to the decline in screening rates at the end of the year—a period when screenings are typically most concentrated. If individuals who missed their screenings in 2020 ultimately received them during the extended period, failing to account for these delayed screenings could lead to an overestimation of the pandemic's effect. To address this concern, we extend the analysis window to 2020–2021 for individuals who were eligible in 2020.

To do so, we estimate equation 1 using the 2016–2018 cohorts of eligible individuals, with the number of weekly health screenings from year t through June of $t+1$ as the outcome variable. Based

[9] The average number of daily confirmed COVID-19 cases was 1,167.7 in 2020 and 11,048.6 in 2021.

[10] Interpreting the decline in screening rates observed in 2020 as an effect of the pandemic requires assuming that, had the pandemic not occurred, screening rates during the same period would have followed the counterfactual trend. To assess this assumption, we conduct a falsification test using pre-pandemic data from 2018 and 2019. If the decline in screening uptake is truly attributable to the pandemic, no systematic deviation from the counterfactual should appear during the pre-pandemic period. Appendix Figure A3 presents changes in screening rates relative to the counterfactual, obtained by estimating equation 1 using the sample from the past three years. Figures A3(a) and A3(b) show the results for the 2018 and 2019 samples, respectively. While some changes are statistically significant, they exhibit no systematic pattern and remain generally close to zero. These results support the interpretation that the decline in screening uptake observed in 2020 reflects the impact of the pandemic.

on this model, we calculate the counterfactual rates for individuals eligible in 2020 and measure the deviation between the actual and counterfactual rates over the 2020–2021 period.

As shown in Figure 2, the results are similar to those presented in Section 4.2.1. At the end of 2020, screening rates declined sharply following the announcement of the screening period extension. In 2021, screening rates rose above the counterfactual and increased steadily until the end of June, when the extended period ended, resulting in a cumulative change of 0.888 percentage points during weeks 53–78 and –5.680 percentage points overall (until week 78). However, it remains unclear whether the extension mitigated the decline in screening rates caused by the pandemic. Its effectiveness depends on both the anticipatory effect of the extension and the increase in screenings during the extended period. Unfortunately, the anticipatory effect cannot be separately identified from individuals' responses to the pandemic itself. Nevertheless, accounting for the extended period helps mitigate the overestimation of the pandemic's effect.

4.2.3 Response to COVID-19 by Predicted Chronic Disease Risk

Figure 3 plots β_1^j from equation 2 across quintiles of predicted risk for chronic diseases.[11] In Figure 3(a), we observe that as the predicted risk for hypertension increases, the probability of receiving a health screening decreases more sharply relative to the first quintile. Specifically, while the reference group (1st quintile) shows a decline of 4.38 percentage points, the probability of screening decreases by an additional 0.9 percentage points in the 2nd quintile (approximately 20% of the effect for the reference group) and by 2.30 percentage points in the 5th quintile (approximately 53%). It is important to note, however, that while the interaction terms for each quintile are statistically significant, the confidence intervals across groups overlap. A qualitatively similar pattern is observed in Figure 3(b), which examines heterogeneity based on predicted risk for diabetes. However, the between-group differences are smaller in magnitude compared to those observed for hypertension. Taken together, these results suggest that individuals at higher risk for chronic disease experienced greater reductions in screening rates during the pandemic.

[11] Baseline estimates from the individual-level analysis that do not allow for differences in responses by chronic disease risk are presented in Appendix Table A3.

While potential risks are relatively easy to interpret, further insight into the patterns observed in Figure 3 can be gained by examining differences in the specific predictors used to estimate these risks. To this end, we first convert the predictors into simplified categorical variables to facilitate the presentation of results. Next, we calculate the average potential risk for each group. Finally, we estimate the decline in the probability of screening by allowing the effect of the pandemic to vary with each predictor of interest.

Figure 4 presents the predicted risk of hypertension for each group alongside the corresponding decline in the probability of screening. Figure 4(a) displays the results of the heterogeneity analysis based on demographic variables, showing that the probability of screening tends to decline more among higher-risk groups. Notably, elderly individuals (aged 60 or older) and medical aid beneficiaries experience a marked decline despite their elevated risk of hypertension. Figure 4(b) presents the results based on information from past screenings. Again, we observe a clear decline in the probability of screening among higher-risk groups. In particular, individuals identified as at-risk based on biomarkers—such as BMI, fasting blood glucose (Glu.), and blood pressure (BP)—are less likely to receive screening, despite their heightened health risk. Similar patterns are observed when the same analysis is conducted using diabetes risk (Appendix Figure A4).

In the context of Korea, where strict quarantine policies—such as mobility restrictions—were not implemented, the results in this section suggest that voluntary responses to the COVID-19 pandemic reduced screening among those most likely to benefit from it.

5 Health Screening and Chronic Disease Management During the COVID-19 Pandemic

In this section, we analyze how delays in health screening during the COVID-19 pandemic affected the initiation of health care utilization related to hypertension and diabetes. This question is particularly relevant for two reasons. First, it allows us to quantify the cost of voluntary responses to the pandemic, which is meaningful in itself, as it captures the health consequences of individuals'

decisions in response to infection risk. Second, it helps us understand whether the reduction in screening disproportionately affected individuals who were most likely to benefit from it. As shown in Section 4.2.3, the decline in screening rates during the pandemic was greater among those at higher risk for chronic diseases. According to the performance comparison of the risk prediction models, biomarkers collected from prior health screenings—such as blood pressure, blood glucose, and BMI—play a critical role in predicting chronic disease risk (Appendix Table A2). Importantly, this information is also observable to individuals themselves. Therefore, despite the greater reduction in screening observed among high-risk individuals, they may have relied on previously available information to manage their chronic disease.

5.1 Empirical Approach

5.1.1 Propensity Score Matching

Our main interest lies in the cost associated with reduced screening rates during the pandemic. Given this objective, our target estimand is the ATU. In the context of this study, the ATU represents how the outcome would have changed if individuals who did not receive a health screening had received one.[12] Specifically, the ATU is defined as follows:

$$\tau_{ATU} = E[\tau \mid D = 0] = E[Y(1) \mid D = 0] - E[Y(0) \mid D = 0] \tag{3}$$

where τ is the treatment effect; D denotes the treatment—in this case, health screening—and $Y(1)$ and $Y(0)$ are the potential outcomes of receiving and not receiving the treatment, respectively.[13] We cannot observe $E[Y(1) \mid D = 0]$ in equation 3—that is, the potential outcome for individuals who did not receive a health screening, had they received one. What we do observe in the data are

[12] This section follows Cunningham (2021) and Shin (2022).

[13] Based on the results in Section 4.2.2, individuals who received a health screening between January 2020 and June 2021 are classified as treated, while those who did not are classified as untreated.

$E[Y(1) \mid D = 1]$ and $E[Y(0) \mid D = 0]$. When we compare these two observable outcomes:

$$E[Y(1) \mid D = 1] - E[Y(0) \mid D = 0] = \tau_{ATU} + \{E[Y(1) \mid D = 1] - E[Y(1) \mid D = 0]\} \quad (4)$$

If $E[Y(1) \mid D = 1] - E[Y(1) \mid D = 0] \neq 0$, the ATU estimate will be biased due to selection. Because individuals can choose whether to receive a health screening, systematic differences may exist between those who were screened during the pandemic and those who were not. These differences may include health status, prior health care utilization, health behaviors, and other factors that influence chronic disease risk. Therefore, the selection bias term is expected to be non-zero.[14]

Propensity score matching can be used to estimate the ATU under two identifying assumptions. The first is the conditional independence assumption, which implies that, conditional on the propensity score, treatment assignment is as good as random. Although this assumption is inherently untestable, we argue that it is plausible in our setting, as propensity score matching balances a rich set of covariates related to health screening and chronic disease between treated and untreated individuals. The second assumption is common support, which requires that, for each value of the propensity score, there exist both treated and untreated individuals. To assess whether this condition is met, we examine the overlap in the distribution of propensity scores between the two groups.

There are two key considerations in selecting covariates for estimating the propensity score. First, following Heckman and Navarro-Lozano (2004), we include covariates that are strongly correlated with the outcome variables—namely, hypertension and diabetes. Second, as emphasized by Caliendo and Kopeinig (2008), only covariates that are not affected by the treatment should be used in estimating the propensity score. Taken together, these considerations support the use of the covariates employed in our risk prediction model for propensity score matching. These covariates are highly predictive of hypertension and diabetes, as demonstrated by model performance (Appendix

[14] According to Appendix Tables A4, individuals who did not receive a health screening tend to have a higher average risk of chronic disease. Therefore, if these individuals had received a screening, their health care utilization related to chronic disease would likely have been higher than that of those who were actually screened. In this case, the direction of selection bias would be negative.

Table A2), and are measured prior to the receipt of health screening.

Next, we describe the matching algorithm used in our analysis. We employ 1:4 nearest neighbor matching, in which each individual in the reference group—the untreated in the ATU framework—is matched to the four treated individuals with the closest propensity scores. Because the number of treated individuals exceeds that of untreated individuals, we allow for replacement to avoid sensitivity to the ordering of observations. To restrict the matching distance, we apply a caliper of 0.2 standard deviations of the propensity score, following Austin (2011). Standard errors are computed using the method proposed by Abadie and Imbens (2006).

Reverse causality between health screening and health care utilization for chronic conditions is a potential concern. Specifically, if an individual initiates health care use for a chronic condition prior to receiving a screening, the incentive to undergo screening may diminish, reducing the likelihood of uptake (Appendix Figure A5). In such cases, the estimated effect of health screening may be downward biased. To address this concern, we adopt two strategies. First, we exclude individuals whose health care utilization began before the month of their screening. For untreated individuals, we exclude those whose health care use began before the month of their previous screening.[15] Second, we include the month of the previous screening as a matching covariate. Individuals screened later in the year have more time for chronic conditions to naturally emerge. Therefore, matching on the month of the previous screening enables comparisons across groups with similar probabilities of natural disease onset.

5.1.2 Event Study

Complementing the propensity score matching, we employ an event study approach that exploits variation in both the timing and receipt of health screenings across individuals. This approach addresses concerns that PSM, while carefully balancing observed characteristics, may still be subject to residual selection. For instance, while the chronic disease risk factors included in the matching procedure capture actual vulnerability to COVID-19, they do not necessarily align with

[15] In the 2016–2019 sample of individuals who received a screening, Appendix Figure A6 shows a strong association between the timing of the previous screening (1–2 years earlier) and that of the current screening.

individuals' perceived risk of infection. Moreover, other unobserved sources of heterogeneity may persist. The event study enhances credibility by examining dynamic changes in care initiation around the screening month. It allows us to test for pre-trends and conduct placebo analyses. These exercises assess whether any remaining source of selection systematically affected the treated and untreated groups. For this analysis, we transform the sample used for propensity score matching into individual-month-level data.[16] We then estimate the following model:

$$Y_{it} = \beta_0 + \sum_{\substack{j=-12 \\ j\neq -1}}^{6} \beta_1^j 1[t - t_i^* = j] + \gamma' X_i + \tau_t + \epsilon_{it} \tag{5}$$

where i indexes individuals and t denotes year-months. We estimate the model using two types of outcome variables (Y_{it}): a dummy variable for the initiation of health care use and a count variable for the number of such uses, each defined separately for hypertension and diabetes. $1[t - t_i^* = j]$ is a dummy variable that equals 1 if j months have passed since the health screening. One month prior to screening ($t = -1$) is used as the reference period; thus, β_1^j captures the change in the outcome relative to this baseline. To control for individual characteristics associated with health care utilization, we include X_i, which consists of the same covariates used in equation 2. τ_t denotes year-month fixed effects. Standard errors are clustered at the individual level.

The coefficient of interest, β_1^j, in equation 5 captures the causal effect of screening, under the assumption that the outcome variables would have followed a smooth trend over time in the absence of screening. To support the validity of this assumption, we provide two pieces of evidence. First, the estimated coefficients β_1^j are close to zero during the pre-screening period. Second, we conduct a placebo test by assigning a false screening month to untreated individuals, matching them to treated counterparts using propensity scores. Since we use 1:4 nearest neighbor matching, the false screening month is randomly drawn from one of the four matched treated individuals.

[16] For a balanced sample, the observation period is limited to 12 months before and 6 months after the health screening.

5.2 Effects of Health Screening on Chronic Disease Care

5.2.1 Matching Details

We begin by assessing the validity of the common support assumption through a visual inspection of the propensity score distribution (Figure 5(a)). As expected, the distribution for the untreated group is somewhat more concentrated at lower values of the propensity score. A common approach to evaluating the common support assumption is to compare the minimum and maximum propensity scores across groups (Caliendo & Kopeinig, 2008). This involves removing observations whose scores fall outside the range of the opposite group. Applying this criterion results in the exclusion of only two treated individuals.

Next, we assess whether the matching procedure effectively balances covariates between individuals who received health screenings and those who did not. To do so, we use the standardized bias measure proposed by Rosenbaum and Rubin (1985):

$$\frac{\bar{x}_{i1} - \bar{x}_{i0}}{\sqrt{(s_{i1}^2 + s_{i0}^2)/2}} \times 100 \tag{6}$$

where $\bar{x}_{i1}$ and $\bar{x}_{i0}$ denote the means of covariate i in the treated and untreated groups, respectively, and s_{i1} and s_{i0} are their corresponding standard deviations.

Although there is no theoretical justification for this threshold, it is conventionally accepted that an absolute standardized difference greater than 20 is considered too large (Shin, 2022). The differences in covariates between the treated and untreated groups, observed before matching, are substantially reduced after matching and fall well below the 20% threshold (Figure 5(b)). These results suggest that the assumption of conditional independence is likely to hold, given that rich covariates related to chronic disease care are used in the matching process and are successfully balanced.

5.2.2 PSM Estimates

Table 2 presents estimates of the average treatment effect of health screening on health care utilization related to chronic diseases among the untreated. According to the baseline model, receiving a health screening increases the probability of initiating hypertension-related care by 2.58 percentage points, corresponding to approximately 35% of the untreated group mean. The number of care visits also increases by 0.217, or about 46% of the untreated mean. For diabetes, the probability of initiating care increases by 2.42 percentage points, and the number of visits increases by 0.098—equivalent to 35% and 41% of the untreated group mean, respectively.[17] To address potential reverse causality, Model (2) excludes individuals whose health care use for the relevant condition began before the screening month. Model (3) includes the month of the previous screening as a matching covariate. The results remain robust to both alternative approaches.

These estimates reflect two channels through which health screenings affect health care utilization. First, screenings increase contact with health care providers. Providers may bill for same-day visits if they deliver additional medical services—such as diagnoses or prescriptions—beyond the screening itself. Second, information conveyed through screenings may influence subsequent health care utilization (Iizuka et al., 2021; H. B. Kim et al., 2019; Oster, 2018b; Zhao et al., 2013). This informational channel is particularly relevant for individuals whose screening results indicate elevated health risks. Given that the sample in this section includes individuals with biomarkers exceeding diagnostic thresholds, this mechanism is also likely to be at play.

Studies examining the effects of health screenings on health care utilization and outcomes have primarily used regression discontinuity designs that exploit diagnosis cutoffs, making their estimates not directly comparable to ours. Nevertheless, for reference, Iizuka et al. (2021) analyze health care utilization in the context of diabetes and report increases of 4.7 percentage points at the alert cutoff (fasting glucose of 110 mg/dL) and 4.0 percentage points at the risk cutoff (126 mg/dL). These estimates are relatively larger than ours, which is expected, as theirs reflect local effects

[17] Appendix Figure A7 shows robustness to varying the number of matched neighbors (1 to 8) and using matching without ties. These specifications yield results consistent with the baseline estimates.

around specific thresholds, while ours represent ATU without restricting the sample to high-risk individuals based on fasting glucose levels.

5.2.3 Event Study Results

Figure 6 presents the estimated coefficients from equation 5. Figures 6(a) and 6(b) focus on hypertension. We estimate changes in care initiation and the number of care visits following screening, using a sample of individuals with no prior use of care for hypertension and diabetes in the past three years. The probability of care initiation increases by approximately 1.14 percentage points immediately after screening, then drops sharply. The number of care visits also rises by 0.019 in the month of screening and slightly declines thereafter, though it remains elevated. In contrast, the untreated group shows no meaningful changes before and after the false screening month. Figures 6(c) and 6(d) present analogous results for diabetes-related health care utilization.[18]

These event study results yield two key implications. First, they reinforce the causal interpretation of the health screening effects estimated using propensity score matching. Second, they suggest that missed screenings disrupted not only the initiation of care but also continued management.

5.3 Effects of Health Screening by Predicted Chronic Disease Risk

Chronic diseases tend to progress gradually, suggesting that health screenings may have larger effects for individuals at higher risk of developing these conditions. In this section, we examine whether the effects of health screenings differ by chronic disease risk. Specifically, we divide the sample into quintiles based on predicted risk for hypertension and diabetes, and estimate the ATU within each quintile using propensity score matching.

[18] Additionally, we employ the Interaction-Weighted (IW) estimator following Sun and Abraham (2021), which accounts for heterogeneous treatment timing, as individuals differ in the month they received screening. For this analysis, we combine the treated and untreated groups into a single sample. Following the implementation of the IW estimator in Sun and Abraham (2021), untreated individuals—who never received a screening—are included as the control group. Because no screening month is defined for these individuals, all event time dummies (leads and lags) are equal to zero, allowing them to serve as the baseline cohort in the estimation. We then estimate the effect using a two-way fixed effects model and the IW estimator. The results are nearly identical to the baseline findings (Appendix Figure A8).

Estimates using the whole sample mask substantial heterogeneity. Figure 7(a) shows that the magnitude of the estimates increases markedly with risk level. In the lowest risk quintile (Q1), the probability of initiating hypertension-related care increases by approximately 0.4 percentage points when the untreated group receives a health screening. However, this estimate is not statistically significant at the 95% confidence level, and a similar result is observed in Q2. From Q3 to Q5, the ATU estimates rise steeply, reaching 6.9 percentage points in Q5—equivalent to approximately 43% of the untreated group mean. A comparable gradient is observed in Figure 7(b) for the number of care visits. Figures 7(c) and 7(d) display qualitatively consistent patterns for diabetes-related outcomes.

When considered alongside the results in Section 4.2.3, which show a greater decline in the probability of screening among individuals at higher risk for chronic disease, these findings suggest that voluntary responses to COVID-19 disproportionately harmed those most likely to benefit from health screening.

5.4 Health Consequences of Delay in Care Initiation

In the previous analyses, we showed that screening increased the likelihood of initiating care for chronic conditions. A relevant follow-up question is whether screening also facilitated earlier detection—specifically, whether untreated individuals began care at a more advanced stage of disease. To address this, we examine the presence of complications associated with hypertension and diabetes, respectively.

Table 3 reports the effects of health screening on the presence of chronic disease complications among new health care users. In the baseline model, receiving a health screening would have reduced the probability of initiating hypertension-related care with complications by 5.72 percentage points, equivalent to approximately 20% of the untreated group mean. This effect is statistically significant. Similarly, for diabetes, the probability of initiating care with complications would have decreased by 2.94 percentage points, or about 13% of the untreated group mean.[19] As in Table 2, which

[19]Matching details for the baseline model are provided in Appendix Figure A9. The results support the common

examines the effects of screening on care initiation, we address the issue of reverse causality here as well. Model (2) excludes individuals who began health care for hypertension or diabetes before screening. Model (3) includes the timing of the previous screening as a matching covariate. The results are robust across both specifications.

This study analyzes the effects of screening within a two-year observation window. While this period is relatively short given the typically long asymptomatic course of chronic diseases, prior research highlights the importance of early detection. For instance, in the case of diabetes, the time from disease onset to diagnosis can range from four to seven years (Harris et al., 1992). Nonetheless, timely diagnosis and initiation of lifestyle or pharmacological interventions can substantially improve outcomes. Harris and Eastman (2000) emphasize that diabetes-related complications may advance significantly during the undiagnosed period, underscoring the value of screening. Even a one-year delay in treatment intensification can elevate the risk of complications, including cardiovascular events (Reach et al., 2017). Similarly, early detection and treatment of hypertension are critical. Martín-Fernández et al. (2019) show that all-cause mortality increases markedly when the interval between diagnosis and blood pressure control exceeds 125 days. Although our results are not directly comparable to these studies due to the shorter follow-up period, the findings in Table 3 suggest that, had the untreated group been screened, chronic disease management may have begun at a less severe stage.

6 Conclusion

This study provides a comprehensive analysis of how individuals' voluntary responses to the COVID-19 pandemic influenced general health screening, a key component of preventive health care. Using a modified interrupted time series approach, we find that participation among eligible individuals declined substantially in 2020, the first year of the pandemic. The richness of the NHIS data allows us to move beyond aggregate patterns and examine heterogeneity in responses based on

support assumption and indicate that covariate imbalance is eliminated after matching. Similar findings hold for Models (2) and (3); results available upon request.

individuals' predicted risk of chronic disease. We find that screening participation declined more sharply among those at higher risk without prior diagnoses of hypertension and diabetes, suggesting greater reductions among those most likely to benefit.

We next examine how reduced screening participation during the pandemic affected chronic disease management. Our findings show that individuals who missed screenings in 2020 would have been more likely to initiate care for hypertension and diabetes if they had received screening. Delays in disease management can lead to deterioration in health. Specifically, individuals who missed screenings were more likely to present with hypertension- and diabetes-related complications when initiating care. Based on our estimates, reduced screening in 2020 led to approximately 262 missed hypertension cases and 246 missed diabetes cases in our sample. Given that the sample represents roughly 4% of the national population, this implies approximately 6,550 missed hypertension cases and 6,144 missed diabetes cases nationwide.[20] These missed cases are estimated to have resulted in approximately 373 cases of hypertension and 178 cases of diabetes, both with complications.[21]

Our study points to a broader implication for health policy: even in the absence of strict quarantine policies, individuals' voluntary responses to infection risk can reduce the uptake of preventive care and, ultimately, worsen health outcomes. Importantly, depending on the nature of the infectious disease, those who are most likely to benefit from preventive care may exhibit the largest declines in utilization. These findings underscore the need for active public health interventions to sustain preventive care during health crises.

[20] We performed a back-of-the-envelope calculation, multiplying the number of eligible individuals by the estimated reduction in screening participation during the pandemic (0.0511) and the ATU for care initiation (0.0258 for hypertension, 0.0242 for diabetes). While these figures illustrate the costs of missed screenings, we do not attempt a formal cost–benefit calculation. Reliable hazard estimates linking diagnostic delays to health outcomes are scarce. Any net-impact calculation would therefore hinge on unverifiable assumptions about the functional relationship between diagnostic delay and disease progression. To avoid over-interpretation, we refrain from speculative monetization.

[21] Applying the estimated ATU for complications to the counterfactual group of missed cases requires the assumption that, in terms of disease progression, these individuals resemble those who initiated care without screening during the observation window. This assumption can be challenged in both directions. On the one hand, missed cases may present with more advanced disease due to longer delays, in which case the effect of screening would be larger in this group than in our study sample. On the other hand, they may exhibit lower severity due to weaker symptoms or slower disease progression that did not yet necessitate care, in which case the screening effect in this group would be smaller than in our study sample. For this reason, the calculation is not intended to provide a point estimate of complications that could have been mitigated. Instead, it serves to illustrate the potential scale of health consequences arising from reduced screening participation.

While our findings benefit from the institutional setting of Korea's National Screening Program—characterized by universal coverage, zero cost, and high accessibility—this context also limits external validity. The results are particularly relevant to health systems with national screening programs, such as those in England and Japan (Fujimaru et al., 2019; Tanner et al., 2022). By contrast, in countries with greater cost-sharing and more fragmented access, the pandemic's impact on screening participation and chronic disease management may differ both in magnitude and in mechanism. Our findings are therefore specific to settings with minimal barriers to care and underscore the need for further research on less supportive systems.

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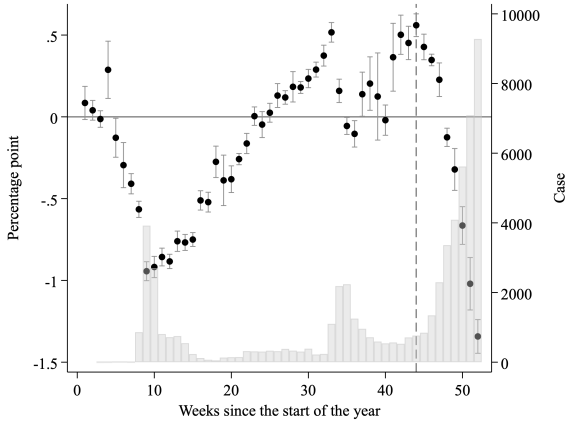
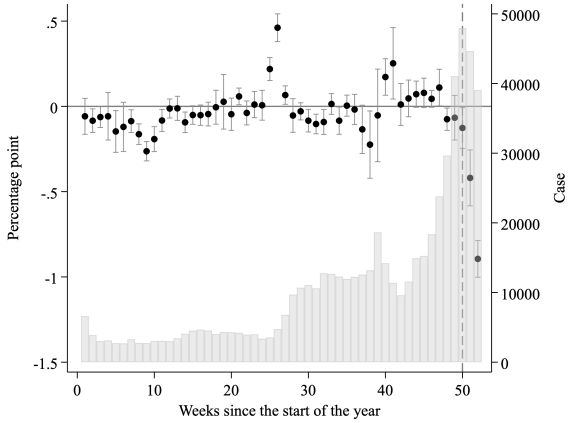
Figures

Figure 1: Change in Health Screening Rates During the COVID-19 Pandemic

(a): Sample from 2020

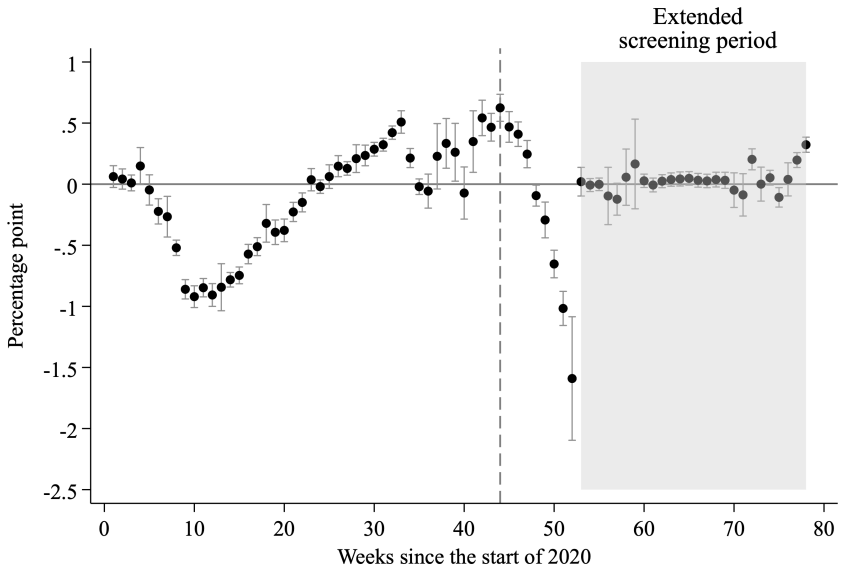


(b): Sample from 2021



Notes: Figures 1(a) and 1(b) show weekly changes in health screening rates relative to the counterfactual for 2020 and 2021, respectively, along with 95% confidence intervals. The counterfactual values are derived by fitting equation 1 to data from 2017 to 2019. Gray bars indicate the number of newly confirmed COVID-19 cases per week, and vertical dashed lines mark the week when the screening period extension was announced. In Figure 1(a), cumulative reductions in screening rates amount to 9.378 percentage points by week 22 (end of the first-wave decline), 4.045 by week 47 (end of the recovery), and 7.520 by week 52 (year-end). Standard errors are robust to heteroskedasticity. Source of COVID-19 case data: World Health Organization and Various sources (2025).

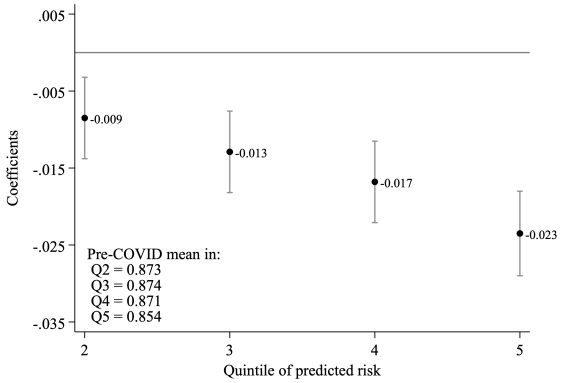
Figure 2: Change in Health Screening Rates for 2020 Cohort with Extended Screening Period



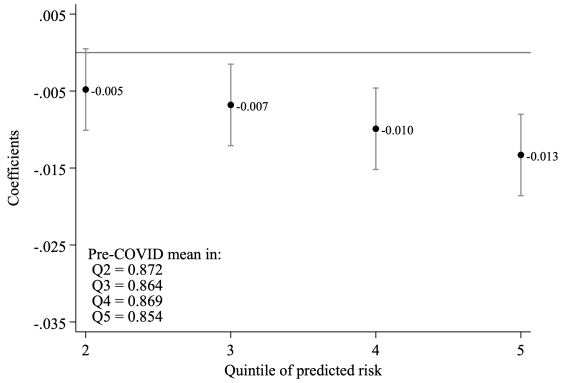
Notes: Figure 2 shows weekly changes in health screening rates in 2020 relative to the counterfactual rates, along with 95% confidence intervals. Vertical dashed lines mark the week when the screening period extension was announced. The counterfactuals are estimated by fitting equation 1 to weekly data from the 2016–2018 cohorts, tracking screening uptake from the eligible year through June of the following year. The cumulative reduction in screening rates reached –6.568 percentage points by week 52. During the extended screening period (shaded area), screening rates increased by 0.888 percentage points, resulting in a total reduction of 5.680 percentage points by week 78. Standard errors are robust to heteroskedasticity.

Figure 3: Heterogeneous Responses by Predicted Chronic Disease Risks

(a): By hypertension risk quintile



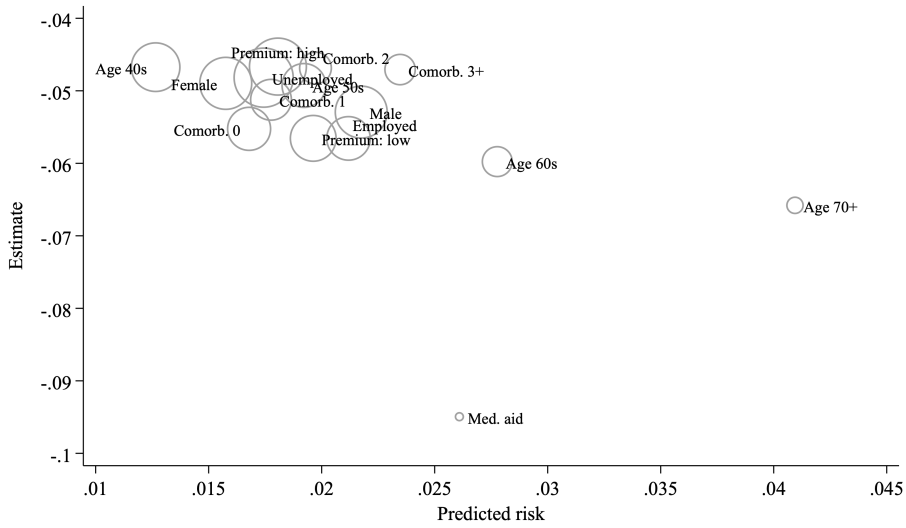
(b): By diabetes risk quintile



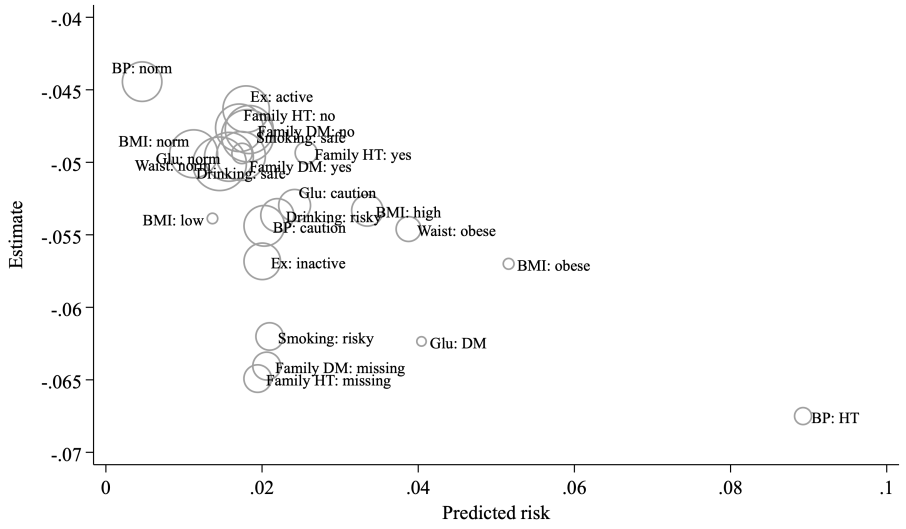
Notes: We estimate equation 2 using a sample of individuals who received a health screening within the past one to two years and had no health care utilization for either hypertension and diabetes in the previous three years. The outcome variable equals 1 if the individual received a screening between year t and June of year $t + 1$. Figures 3(a) and 3(b) present the estimated coefficients, allowing the change in the probability of receiving a screening during the pandemic to vary across quintiles of predicted risk for hypertension and diabetes, respectively. The method used to construct the predicted risk is described in Appendix A. The first quintile serves as the reference group and is omitted from the figures. The estimated decrease in screening probability for the reference group (first quintile) is –0.0385 for hypertension and –0.0438 for diabetes. Standard errors are robust to heteroskedasticity.

Figure 4: Breakdown by Variables Used in Risk Prediction (Hypertension)

(a): Demographic variables



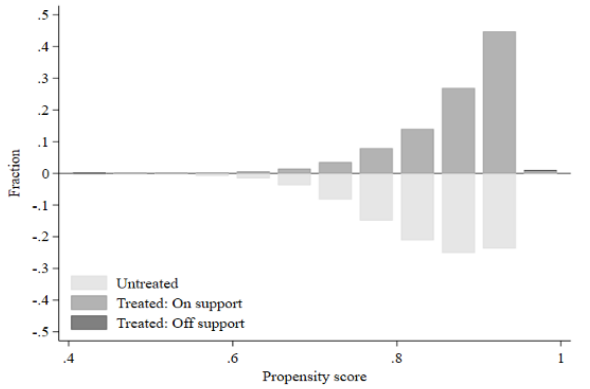
(b): Variables from Past Health Screenings



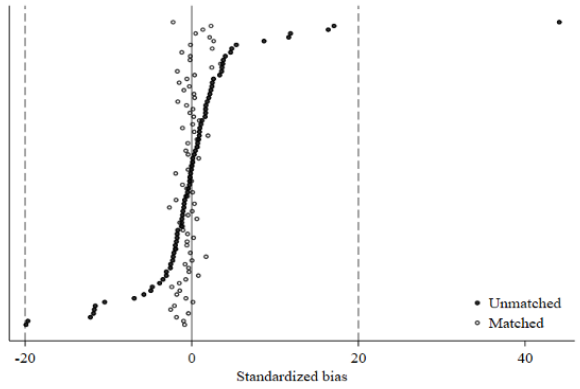
Notes: Figure 4 shows the results of a heterogeneity analysis based on the variables used to predict hypertension risk. For each variable, we estimate equation 2, allowing the effect of the pandemic on the probability of receiving a screening to vary across groups. The horizontal axis represents the average predicted risk for each group, and the vertical axis indicates the estimated change in screening probability during the pandemic, relative to the pre-pandemic period. For presentation purposes, the original variables used in the risk prediction model (see Appendix Table A1) are grouped into simplified categories. The size of each circle is proportional to the sample size of the corresponding group.

Figure 5: Validity of Propensity Score Matching

(a): Distribution of propensity score



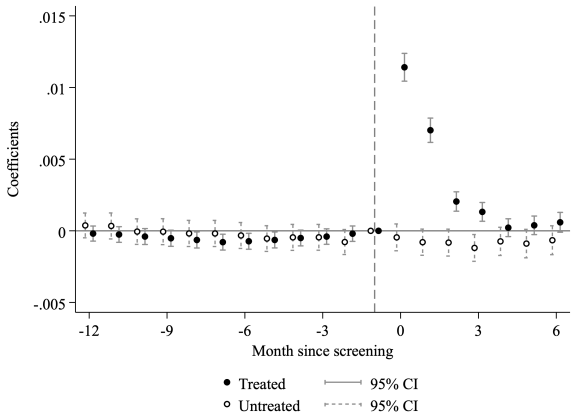
(b): Balance in covariates: standardized bias



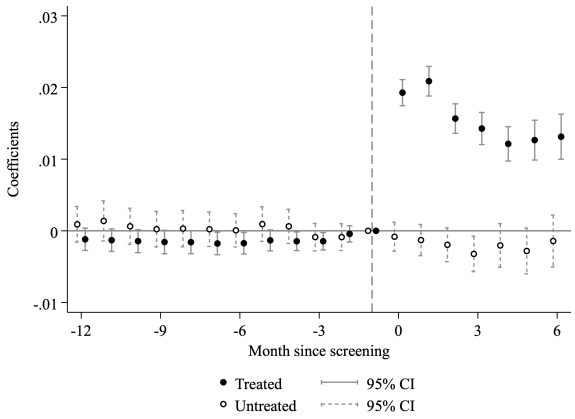
Notes: Figure 5(a) shows the distribution of propensity scores for the treated and untreated groups. Following Caliendo and Kopeinig (2008), we assess the common support assumption by comparing the minimum and maximum values of the propensity score distributions across groups. The matched sample includes 172,508 treated individuals (2 excluded due to lack of common support) and 26,212 untreated individuals (none excluded). Figure 5(b) presents the standardized bias of covariates before and after matching. Matching was performed using the `psmatch2` module in Stata. Because the number of covariates exceeds 30, variable names are not labeled in the plot due to program limitations.

Figure 6: Effects of Screening on Health care Use: Event Study Results

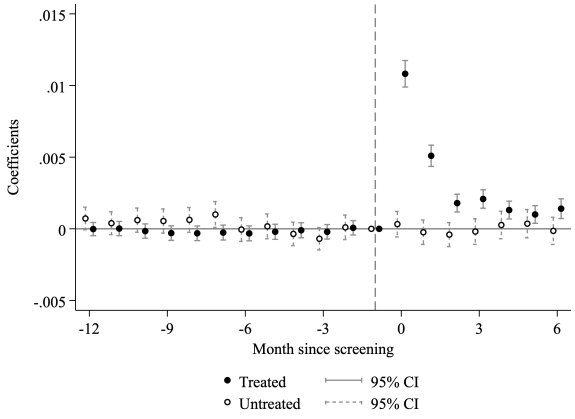
(a): Hypertension - *Care initiation*



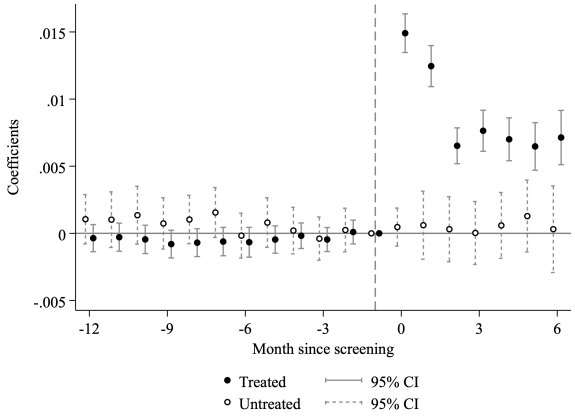
(b): Hypertension - *Number of care visits*



(c): Diabetes - *Care initiation*



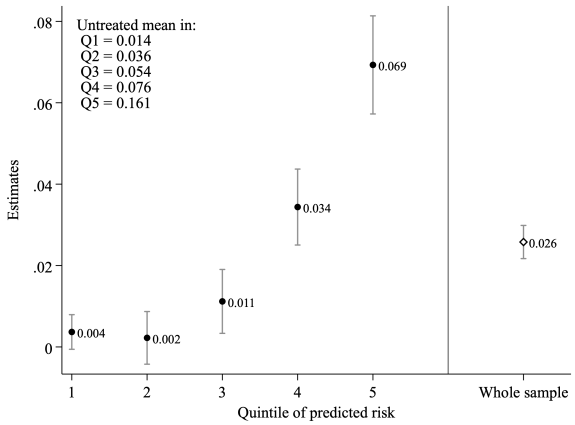
(d): Diabetes - *Number of care visits*



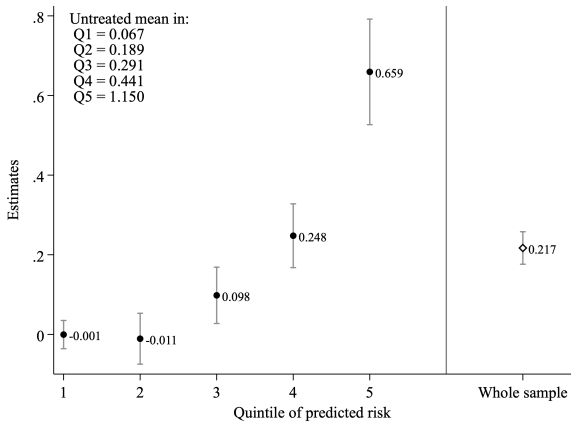
Notes: Figure 6 presents estimates from equation 5, illustrating how health care utilization evolves before and after screening. For the untreated group, a false screening month is assigned by randomly selecting one of four treated individuals matched through propensity score matching. Figures 6(a) and 6(b) use *Care initiation* (a dummy variable indicating the first instance of health care use) and *Number of care visits* (the total number of hypertension-related visits) as outcome variables. Figures 6(c) and 6(d) present analogous results for diabetes-related health care utilization. Standard errors are clustered at the individual level.

Figure 7: Heterogeneous Effects of Health Screening by Chronic Disease Risk

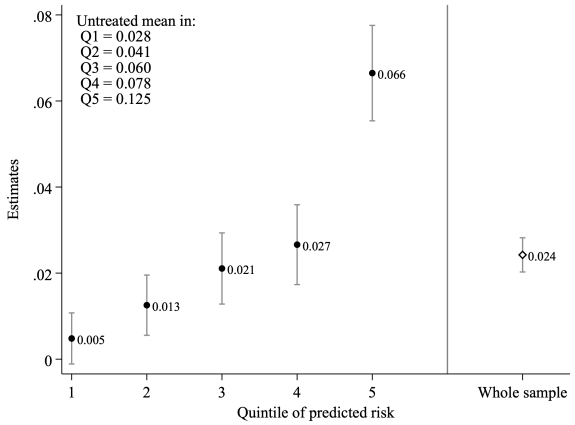
(a): Hypertension - *Care initiation*



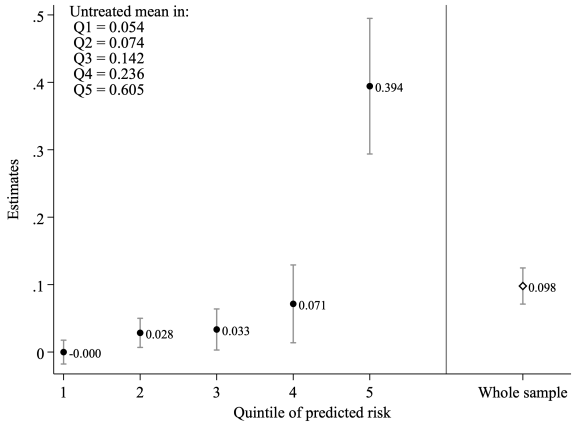
(b): Hypertension - *Number of care visits*



(c): Diabetes - *Care initiation*



(d): Diabetes - *Number of care visits*



Notes: Figure 7 presents average treatment effect on the untreated (ATU) estimates from propensity score matching, stratified by quintiles of predicted risk for hypertension and diabetes. The outcome variable, *Care initiation*, is a dummy equal to 1 if the individual used any health care related to the respective condition, and 0 otherwise. *Number of care visits* refers to the total number of such visits. Outcome variables are measured using medical claims data from 2020 to 2021. Figures 7(a) and 7(b) show results for hypertension-related health care use, and Figures 7(c) and 7(d) present the corresponding results for diabetes. The method for constructing predicted risk is described in Appendix A. Standard errors are calculated following Abadie and Imbens (2006).

Tables

Table 1: Summary of Sample Construction

Section	Sample construction	Unit of analysis	Outcome variable
Section 4. Changes in Health Screening Rates During the COVID-19 Pandemic	- Eligible individuals for health screening, aged 40 to under 80 years - Sample period: 2016–2021	National-level	Number of screenings per 100 eligible individuals
	- Eligible individuals for health screening, aged 40 to under 80 years - Excluding those who utilized health care for hypertension and diabetes in the past three years - Restricted to those who received a health screening within the past two years - Sample period: 2016–2021	Individual-level	Dummy variable for receiving a health screening
Section 5. Health Screening and Chronic Disease Management During the COVID-19 Pandemic	- Based on the individual-level sample in Section 4 - Restricted to the 2020–2021 period	Individual-level	Utilization of health care for: 1) hypertension or diabetes 2) related complications

Table 2: Average Treatment Effects of Screening on Health care Use for Chronic Diseases

	(1) Baseline			(2) Excluding sample diagnosed before screening			(3) Matching on previous screening month		
	N	Mean (untreated group)	Estimate	N	Mean (untreated group)	Estimate	N	Mean (untreated group)	Estimate
Panel A: hypertension									
Outcome variable:									
Care initiation	198720	0.0733	0.0258***	194967	0.0533	0.0266***	198720	0.0733	0.0253***
			(0.0021)			(0.0019)			(0.0021)
Number of care visits	198720	0.4655	0.2170***	194967	0.2790	0.2015***	198720	0.4655	0.2244***
			(0.0208)			(0.0158)			(0.0216)
Panel B: diabetes									
Outcome variable:									
Care initiation	198720	0.0692	0.0242***	195287	0.0513	0.0263***	198720	0.0692	0.0249***
			(0.0020)			(0.0018)			(0.0020)
Number of care visits	198720	0.2377	0.0979***	195287	0.1427	0.1070***	198720	0.2377	0.1024***
			(0.0137)			(0.0098)			(0.0138)

Notes: Table 2 reports average treatment effect on the untreated (ATU) estimates obtained from propensity score matching. The variable *Care initiation* is a dummy equal to 1 if the individual initiated health care use for the respective condition (hypertension or diabetes). The variable *Number of care visits* refers to the total number of related visits. All outcome variables are measured using medical claims data from 2020 to 2021. Model (2) excludes individuals who initiated care for the respective condition prior to receiving a screening. Model (3) additionally includes the timing of the most recent screening as a matching covariate. Standard errors are calculated following Abadie and Imbens (2006). A single asterisk denotes statistical significance at the 90% confidence level; double, 95%; triple, 99%.

Table 3: Average Treatment Effects of Screening on Complications from Chronic Diseases

	(1) Baseline			(2) Excluding sample diagnosed before screening			(3) Matching on previous screening month		
	N	Mean (untreated group)	Estimate	N	Mean (untreated group)	Estimate	N	Mean (untreated group)	Estimate
Panel A: among individuals initiating hypertension care									
Complications	17018	0.2853	-0.0572***	12722	0.2332	-0.0595***	17018	0.2853	-0.0712***
			(0.0122)			(0.0138)			(0.0121)
Panel B: among individuals initiating diabetes care									
Complications	16724	0.2270	-0.0294**	13292	0.2267	-0.0372***	16724	0.2270	-0.0257**
			(0.0115)			(0.0136)			(0.0118)

Notes: Table 3 presents average treatment effect on the untreated (ATU) estimates from propensity score matching, based on a sample of individuals who initiated health care use for hypertension or diabetes in 2020. The outcome variables are two separate dummy variables, indicating whether the individual used health care related to complications from hypertension and from diabetes, respectively. For hypertension, complications include coronary artery disease (I20–I25), cerebrovascular disease (I60–I69), heart failure (I50), and chronic kidney disease (N18, N19), based on the Korean Standard Classification of Diseases (KCD). For diabetes, we include only subcategories within E10–E14 that indicate diabetes with complications. The outcomes are measured using medical claims data from 2020 to 2021. In Model (2), individuals who initiated care prior to screening are excluded. Model (3) additionally includes the timing of the most recent screening as a matching covariate. Standard errors are calculated following Abadie and Imbens (2006). A single asterisk denotes statistical significance at the 90% confidence level, double 95%, and triple 99%.

Appendix

A Risk Prediction

Risk prediction models for hypertension and diabetes typically incorporate a wide range of variables, including biomarkers (e.g., blood pressure and fasting glucose), health behaviors, and family history of these conditions (Collins et al., 2011; Nusinovici et al., 2020; D. Sun et al., 2017). Since the National Health Insurance Service (NHIS) collects detailed health screening data, our dataset includes many of the key predictors commonly used in the existing literature.

The variables included in our prediction model are summarized in Table A1. We begin with demographic variables: age group (in 5-year intervals), sex, insurance premium (in 20th percentiles), and type of health insurance. The health screening database additionally provides information on biomarkers (BMI, waist circumference, blood pressure, and fasting blood glucose), health behaviors (alcohol consumption, smoking, and physical activity), and family history of chronic diseases. Biomarkers are categorized based on clinical diagnostic criteria. We also incorporate health care utilization related to Elixhauser comorbidity conditions into the model (Khan et al., 2018; Uddin et al., 2022).

Logit models perform comparably to machine learning approaches in predicting chronic disease risk (Nusinovici et al., 2020). Accordingly, we use logit models to predict the risk of hypertension and diabetes. The outcome variable is a dummy equal to 1 if an individual initiates health care utilization for hypertension or diabetes as the primary condition in a given year, and 0 otherwise. The model is estimated using a sample of individuals aged 40 to 79 in 2015 who (i) had no prior health care utilization related to hypertension and diabetes in the preceding three years, and (ii) had received a health screening within the past one to two years. We sequentially add groups of predictors. To evaluate model performance, we compare the area under the receiver operating characteristic curve (AUC) across specifications. To guard against overfitting, we use 5-fold cross-validation during model training. The dataset is randomly partitioned into five folds, with each fold serving once as the test set and the remaining four used for training. The AUC values reported in

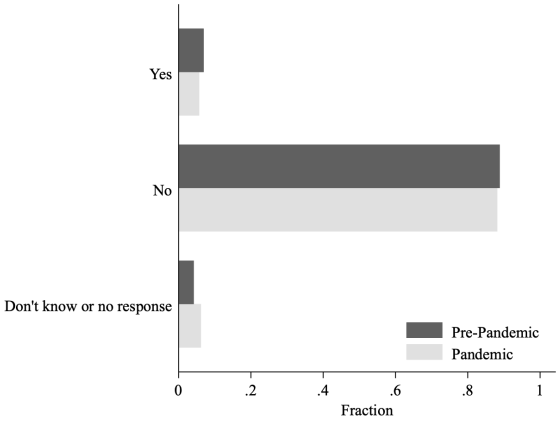
Table A2 reflect the out-of-sample performance, averaged across folds.

Table A2 reports the AUC for each specification. Columns (1) to (5) sequentially add groups of predictors. Notably, the inclusion of biomarkers in Column (2) leads to a substantial improvement in AUC. The subsequent addition of health behaviors, family history, and Elixhauser comorbidity conditions in Columns (3) to (5) yields incremental gains in model performance. In Columns (6) and (7), comorbidity conditions are constructed using information from the past two and three years, respectively. Column (7), which yields the highest AUC, is used in the heterogeneity analysis by chronic disease risk level.

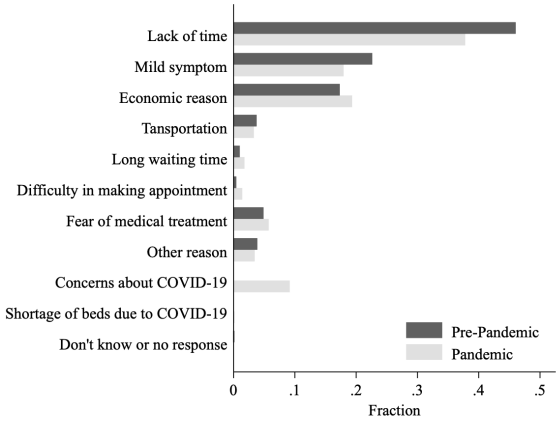
B Figures

Figure A1: COVID-19 Pandemic and Unmet Health care Need

(a): Status of Unmet Health care Needs

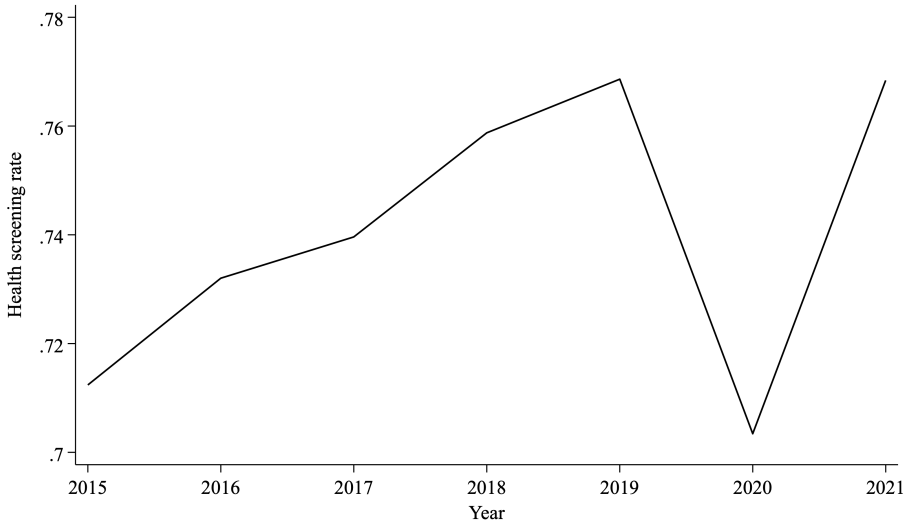


(b): Cause of Unmet Health care Needs



Notes: Figure A1(a) reports the share of individuals who reported needing but not receiving health care in the past year. Figure A1(b) presents the main reasons cited for foregoing care. All proportions are weighted using survey sampling weights. The analysis uses data from the Korea National Health and Nutrition Examination Survey (KNHANES) for the years 2017 to 2021, restricted to individuals aged 40 to 79. The pre-pandemic period is defined as 2017–2019, and the pandemic period as 2020–2021.

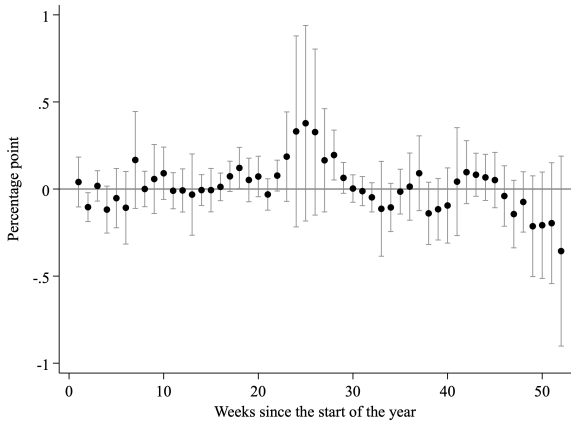
Figure A2: Trends in Health Screening Rates



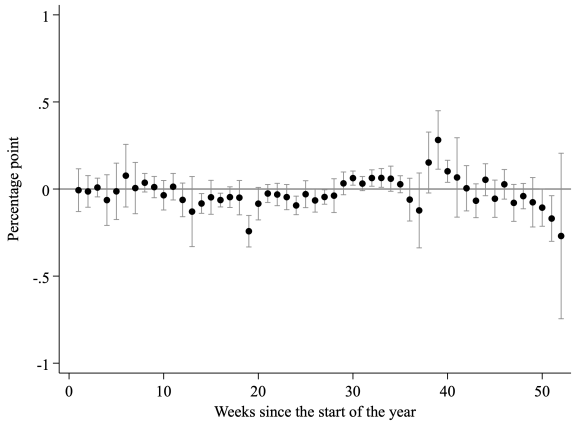
Notes: Figure A2 presents annual trends in the proportion of eligible individuals aged 40 to 79 who received a health screening.

Figure A3: Falsification Test Using Pre-Pandemic Samples

(a): Sample from 2018



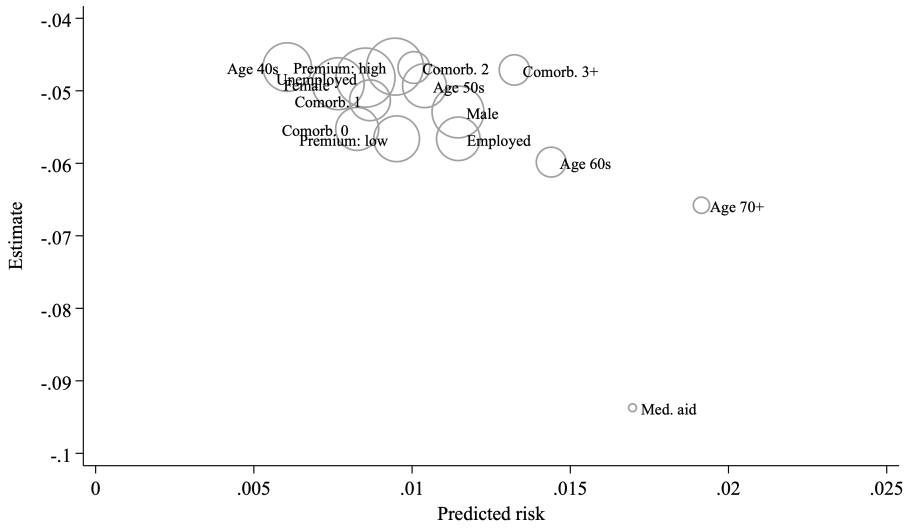
(b): Sample from 2019



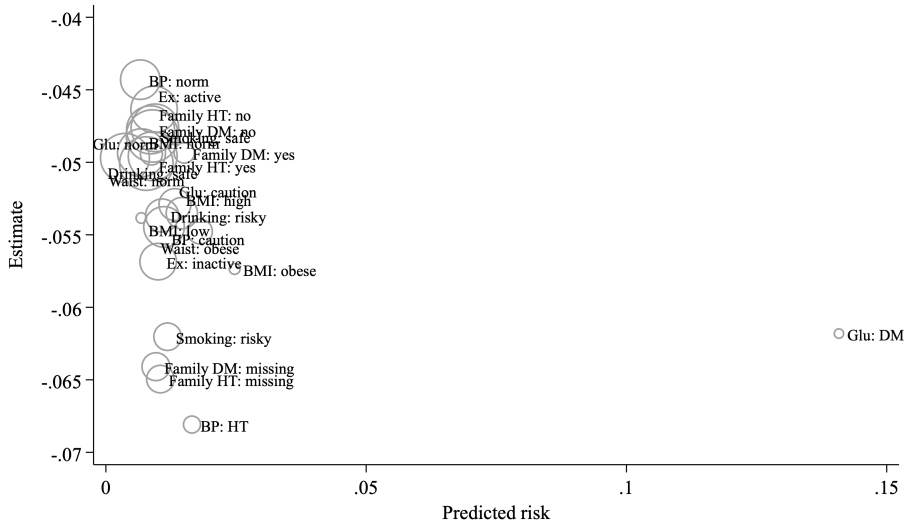
Notes: Figures A3(a) and A3(b) show weekly changes in health screening rates relative to the counterfactual for 2018 and 2019, respectively, along with 95% confidence intervals. The counterfactual values are estimated by fitting equation 1 to data from the preceding three years for each corresponding year (i.e., 2015–2017 for 2018, and 2016–2018 for 2019). Standard errors are robust to heteroskedasticity.

Figure A4: Breakdown by Variables Used in Risk Prediction (Diabetes)

(a): Demographic variables

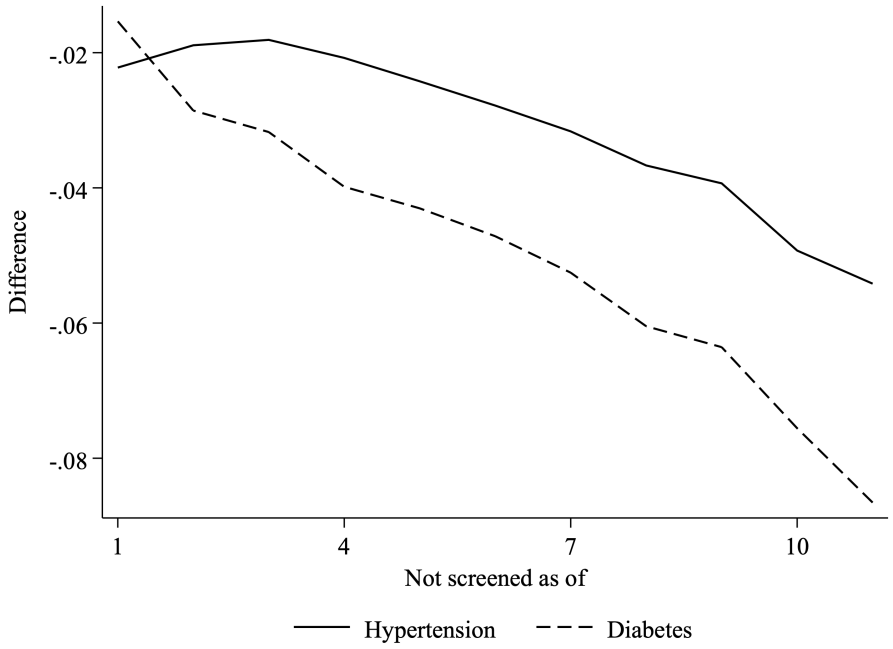


(b): Variables from Past Health Screenings



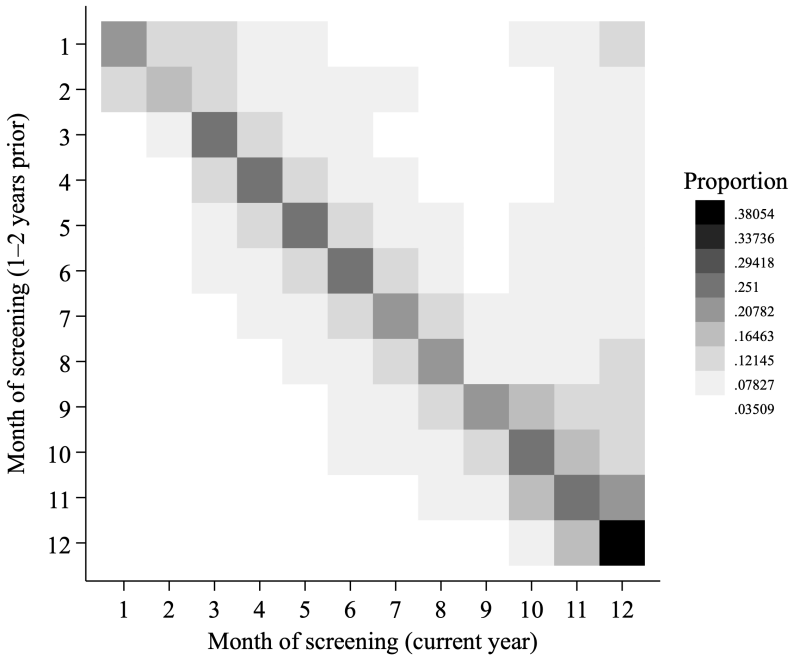
Notes: Figure A4 shows the results of a heterogeneity analysis based on the variables used to predict diabetes risk. For each variable, we estimate equation 2, allowing the effect of the pandemic on the probability of receiving a screening to vary across groups. The horizontal axis represents the average predicted risk for each group, and the vertical axis indicates the estimated change in screening probability during the pandemic, relative to the pre-pandemic period. For presentation purposes, the original variables used in the risk prediction model (see Appendix Table A1) are grouped into simplified categories. The size of each circle is proportional to the sample size of the corresponding group.

Figure A5: Health Screening Rates by Care Initiation Status for Chronic Diseases



Notes: Figure A5 presents differences in screening rates during the designated screening period between individuals who initiated health care for hypertension or diabetes and those who did not, conditional on not having received a screening by each calendar month. The analysis uses pre-pandemic data from 2016 to 2019 and focuses on individuals aged 40 to 79 who had received a screening within the past one to two years and had no health care use related to hypertension and diabetes in the preceding three years.

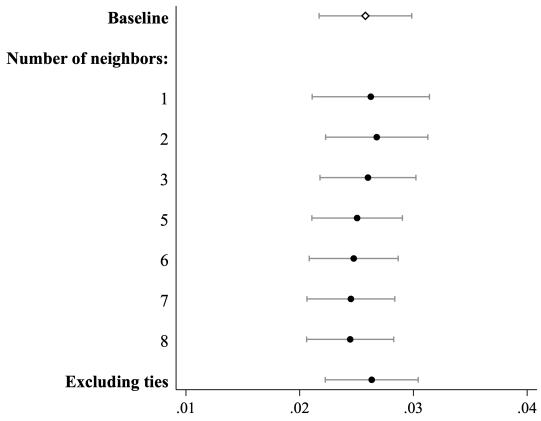
Figure A6: Tabulation of Screening Months in Current and Prior Years



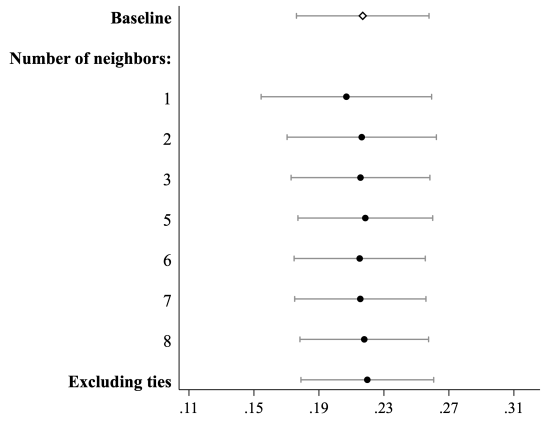
Notes: Figure A6 presents a tabulation of individuals' screening months, comparing the month of screening in the current year with that in the previous one to two years. The analysis uses data from individuals aged 40 to 79 who received health screenings between 2016 and 2019, restricted to those who had undergone a screening within the past one to two years and had no health care use related to hypertension and diabetes in the preceding three years.

Figure A7: Robustness of ATU Estimates on Health care Use

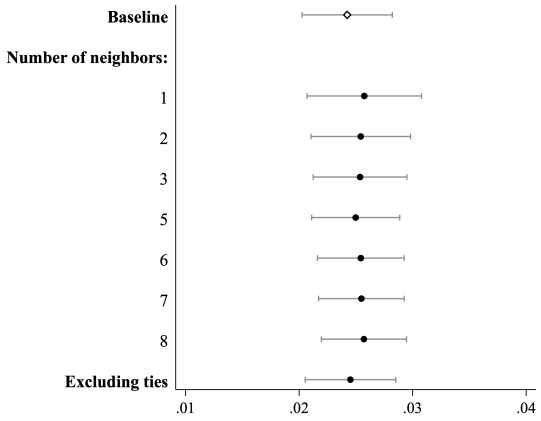
(a): Hypertension - *Care initiation*



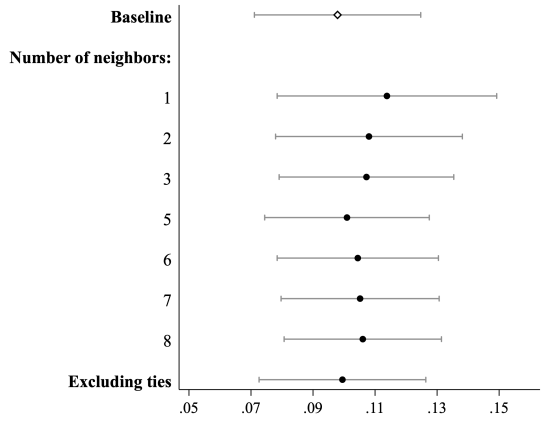
(b): Hypertension - *Number of care visits*



(c): Diabetes - *Care initiation*



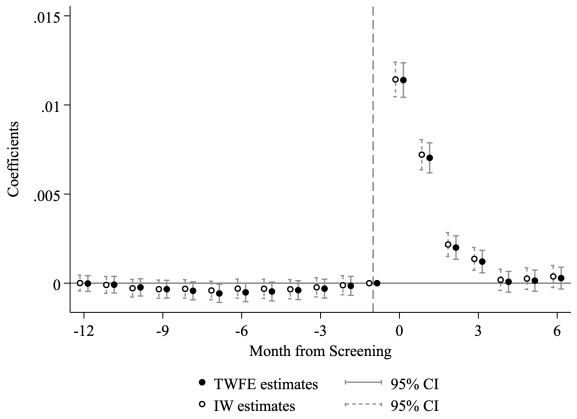
(d): Diabetes - *Number of care visits*



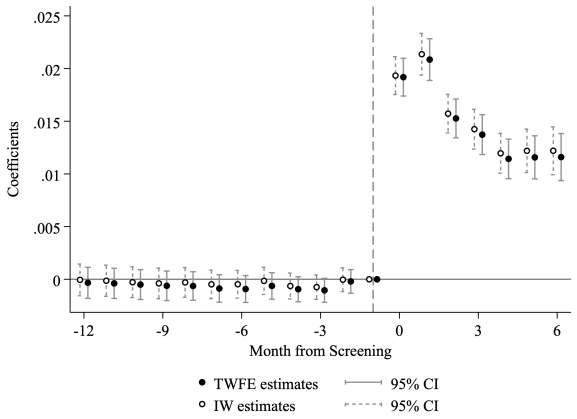
Notes: Figure A7 presents average treatment effect on the untreated (ATU) estimates from propensity score matching, with 95% confidence intervals. The variable *Care initiation* is a dummy equal to 1 if the individual used health care for the respective condition (hypertension or diabetes), while *Number of care visits* denotes the total number of such visits. Outcomes are measured using medical claims data from 2020 to 2021. The baseline specification uses four nearest neighbors and allows for matching with all ties. The group labeled "Number of neighbors" presents estimates obtained by varying the number of neighbors from 1 to 8. The estimate labeled "Excluding ties" is based on matching exactly four neighbors while excluding ties. Standard errors are calculated using the method of Abadie and Imbens (2006).

Figure A8: Comparing Screening Effects: TWFE Model vs. IW Estimator

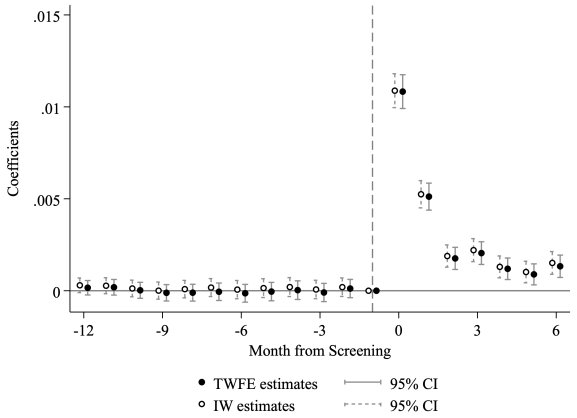
(a): Hypertension - *Care initiation*



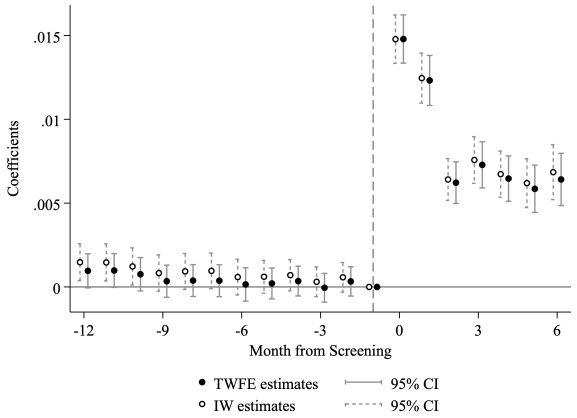
(b): Hypertension - *Number of care visits*



(c): Diabetes - *Care initiation*



(d): Diabetes - *Number of care visits*

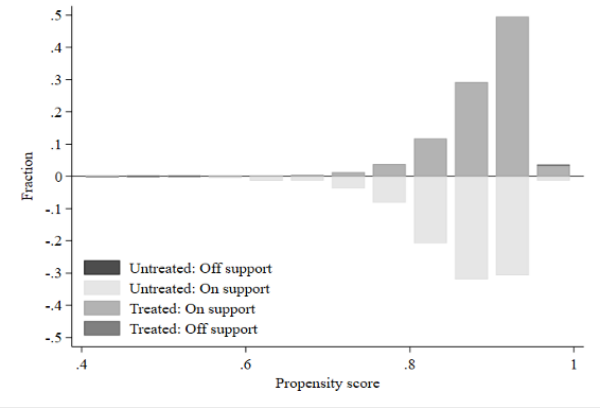


Notes: Figure A8 presents estimates from a two-way fixed effects (TWFE) model and the interaction-weighted (IW) estimator, following L. Sun and Abraham (2021), to compare changes in health care utilization before and after screening. Since no screening month is defined for the untreated group, all event time dummies (leads and lags) are equal to zero, allowing this group to serve as the baseline cohort in the estimation. Figures A8(a) and A8(b) use *Care initiation* (a dummy variable equal to 1 if the individual initiated health care use) and *Number of care visits* (the total number of hypertension-related visits) as dependent variables. Figures A8(c) and A8(d) show the same analysis for diabetes-related health care utilization. Standard errors are clustered at the individual level.

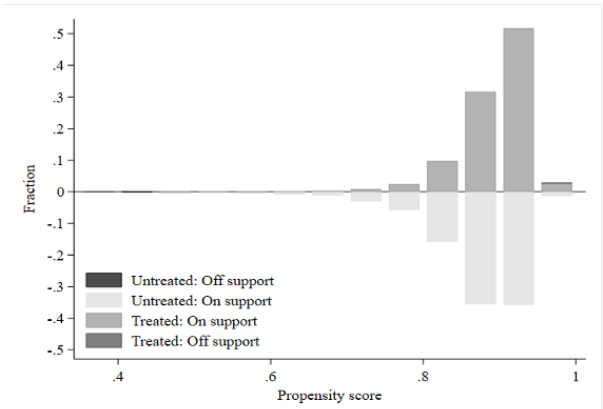
Figure A9: Validity of Propensity Score Matching (Section 5.4)

Distribution of propensity score

(a): Hypertension sample

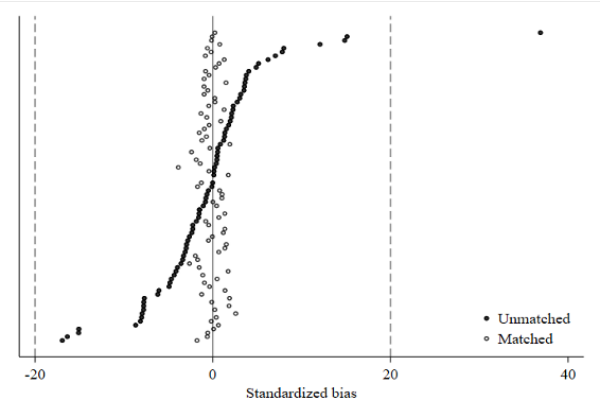


(b): Diabetes sample

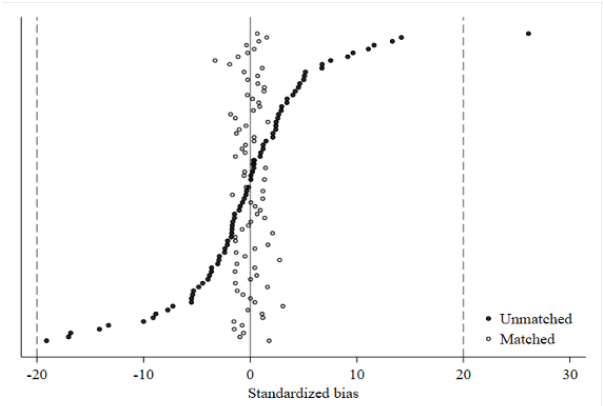


Balance in covariates: standardized bias

(c): Hypertension sample



(d): Diabetes sample



Notes: Figure A9(a) shows the distribution of propensity scores for the treated and untreated groups used in the baseline matching for Table 3. Following Caliendo and Kopeinig (2008), we assess the common support assumption by comparing the minimum and maximum values of the propensity score distributions across groups. The matched sample includes 15,097 treated individuals (20 excluded due to lack of common support) and 1,921 untreated individuals (1 excluded). Figure A9(b) shows the same assessment for diabetes sample, consisting of 14,909 treated individuals (37 excluded) and 1,815 untreated individuals (2 excluded). Figures A9(c) and A9(d) present the standardized bias of covariates before and after matching. Matching was performed using the `psmatch2` module in Stata. Because the number of covariates exceeds 30, variable names are not labeled in the plot due to program limitations.

Tables

Table A1: List of Variables Used in Risk Prediction

Category	Variable	Description
Outcome variable	Health care use related to hypertension, diabetes	Dummy variable indicating health care utilization with hypertension or diabetes as the primary diagnosis
Demographic variable	Age	Dummy variables for age groups in 5-year intervals
	Health insurance premium	Dummy variables for each of the 21 groups, composed of 20 insurance premium quintiles and medical aid recipients
	Health insurance type	Dummy variable representing employee subscribers
	Sex	Dummy variable equal to 1 for females
Past health screening	BMI	Dummy variables for underweight, normal, cautious, and suspected obesity
	Waist circumference	Dummy variables for normal and suspected abdominal obesity
	Fasting blood sugar	Dummy variables for normal, cautious, and suspected diabetes
	Blood pressure	Dummy variables for normal, cautious, and suspected hypertension
	Physical activity	Dummy variable indicating the need for physical activity
	Smoking	Dummy variable indicating the need for smoking cessation
	Alcohol consumption	Dummy variable indicating the need for abstaining from alcohol
	Family history of hypertension, diabetes	Dummy variable indicating a family history of hypertension, diabetes
Elixhauser Comorbidity Condition	27 disease groups	Dummy variables indicating health care utilization due to the respective condition

Table A2: Comparison of Prediction Model Performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: hypertension							
AUC	0.6356	0.7864	0.7869	0.7892	0.7906	0.7909	0.7911
Panel B: diabetes							
AUC	0.6339	0.8148	0.8150	0.8178	0.8219	0.8247	0.8254
Predictors:							
Demographics	Y	Y	Y	Y	Y	Y	Y
Biomarkers		Y	Y	Y	Y	Y	Y
Health behavior			Y	Y	Y	Y	Y
Family history				Y	Y	Y	Y
Elixhauser comorbidity - 1 year					Y		
Elixhauser comorbidity - 2 years						Y	
Elixhauser comorbidity - 3 years							Y

Notes: Table A2 reports the area under the receiver operating characteristic curve (AUC) from prediction models estimating the initiation of health care utilization for hypertension (Panel A) and diabetes (Panel B). The outcome variable is a dummy equal to 1 if an individual initiated health care use for the corresponding condition as the primary condition in a given year, and 0 otherwise. The models are estimated using logistic regression, with AUC values computed based on 5-fold cross-validation. Each column incrementally adds a group of predictors, including demographics, biomarkers, health behaviors, family history, and Elixhauser comorbidity conditions constructed using data from the past one to three years. A detailed description of each predictor group is provided in Appendix Table A1.

Table A3: Effect of the COVID-19 Pandemic on Health Screening Participation: Baseline Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
COVID	-0.0117***	-0.0518***	-0.0534***	-0.0531***	-0.0513***	-0.0511***	-0.0511***
	(0.0009)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)
Controls:							
Year trend		Y	Y	Y	Y	Y	Y
Demographics			Y	Y	Y	Y	Y
Biomarkers				Y	Y	Y	Y
Health behavior					Y	Y	Y
Family history						Y	Y
Elixhauser comorbidity							Y
Adjusted R-squared	.0002	.0011	.0288	.0302	.0315	.0331	.0344
Observations	770815	770815	770815	770815	770815	770815	770815

Notes: Table A3 reports estimates from a series of linear probability models assessing the effect of the COVID-19 pandemic on the likelihood of receiving a health screening among eligible individuals. The outcome variable is a dummy equal to 1 if the individual received a health screening between year t and June of year $t+1$, and 0 otherwise. The variable of interest, $COVID$, is a dummy equal to 1 if the individual was eligible for screening in 2020 and 0 if eligible in 2016–2018. Individuals eligible in 2019 are excluded, as their time window partially overlapped with the early stage of the pandemic. Control variables are added sequentially from Columns (1) to (7), with definitions provided in Appendix Table A1. Standard errors are robust to heteroskedasticity. A single asterisk denotes statistical significance at the 90% confidence level, double 95%, and triple 99%.

Table A4: Sample Characteristics (Section 5)

	Untreated		Treated		Difference
	Mean	SD	Mean	SD	
Outcome variables					
Care initiation (hypertension)	0.073		0.088		-0.014
Number of care visits (hypertension)	0.466	2.505	0.590	2.923	-0.124
Care initiation (diabetes)	0.069		0.087		-0.017
Number of care visits (diabetes)	0.238	1.665	0.286	1.688	-0.049
Demographic characteristics					
Age	53.110	9.008	52.513	8.713	0.597
Health insurance premium (20-quantiles)	11.411	6.305	11.948	5.991	-0.537
Recipient of medical aid	0.020		0.006		0.014
Employee-insured status	0.492		0.703		-0.211
Female	0.524		0.503		0.021
Previous screening results (1–2 years prior)					
Obesity risk status (BMI)					
Underweight	0.033		0.027		0.006
Normal	0.635		0.652		-0.018
Caution	0.291		0.287		0.004
At-risk	0.041		0.034		0.007
Obesity risk status (waist circumference)					
Normal	0.801		0.820		-0.019
At-risk	0.199		0.180		0.019
Diabetes risk status (fasting blood glucose)					
Normal	0.656		0.673		-0.017
Caution	0.316		0.306		0.009
At-risk	0.028		0.021		0.008
Hypertension risk status (blood pressure)					
Normal	0.415		0.458		-0.043
Caution	0.472		0.464		0.008
At-risk	0.112		0.078		0.034
Smoking cessation needed					
No	0.765		0.812		-0.047
Yes	0.235		0.188		0.047
Drinking cessation needed					
No	0.650		0.654		-0.004
Yes	0.350		0.346		0.004
Physical activity needed					
No	0.462		0.521		-0.059
Yes	0.538		0.479		0.059
Family history (diabetes)					
No	0.612		0.693		-0.081
Yes	0.135		0.134		0.001
Missing	0.253		0.173		0.080
Family history (hypertension)					
No	0.592		0.671		-0.079
Yes	0.163		0.164		-0.001
Missing	0.245		0.165		0.080
N	26212		172508		

References for Appendix

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