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# Income Receipt, Economic Activities, and Health: Evidence from Ambulance Transport Patterns

**Yoko Ibuka, Junya Hamaaki**

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Institute for Economic Studies, Keio University
2-15-45 Mita, Minato-ku, Tokyo 108-8345, Japan
ies-office@adst.keio.ac.jp
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Yoko Ibuka
Faculty of Economics, Keio University
2-15-45 Mita, Minato-ku, Tokyo 108-8345, Japan
ibuka@econ.keio.ac.jp

Junya Hamaaki
Faculty of Economics, Hosei University
4342 Aihara, Machida City, Tokyo194-0298, Japan
hamaaki@hosei.ac.jp

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Yoko Ibuka †  Junya Hamaaki ‡

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Studies suggest that mortality increases after income receipt. To examine whether the adverse effect of income on health is induced by economic activities and how certain economic activities are related to specific health conditions, we investigate within-month cycles in ambulance transport, utilizing detailed information on the locations of the origin and timing of the transports. Our analysis exploits the difference in the number of patients on the same day between payment and non-payment months, using the Japanese National Pension for the elderly that is distributed bi-monthly. We observe a 4.5% increase in ambulance transports on the day of pension payment, primarily attributed to heightened economic activities such as gambling or amusement, shopping, and dining out. We have suggestive evidence indicating that this increase in transport is linked to a relaxation in liquidity. These findings have implications for healthcare system preparedness and the optimal design of public benefit payment.

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†Corresponding author. Faculty of Economics, Keio University & Department of Economics, University of Hawaiʻi at Mānoa. 2-15-45 Mita, Minato-ku, Tokyo 108-8345, Japan. Email: ibuka@econ.keio.ac.jp

‡Faculty of Economics, Hosei University. 4342 Aihara, Machida City, Tokyo, 194-0298, Japan. Email: hamaaki@hosei.ac.jp

# 1 Introduction

Recent research has increasingly focused on the causal effects of income on health to better understand the socioeconomic determinants of health and formulate effective designs for public policy. The effects could depend on the duration over which the impact of income receipt is observed because different mechanisms exist within the time frame of health- and non-health-related decision making and the emergence of their consequences. In the medium and long run, it is theoretically expected that income generally encourages health investment, through improved nutrition intake and enhanced preventive care.[1]

For short-term effects, the theoretical expectation is not very clear. Moreover, empirical studies consistently demonstrate a *negative* effect of health, showing that mortality, as an ultimate measure of health status, tends to increase upon income arrival. The negative impact of income receipt on health is crucial for understanding the intricate relationship between economic conditions and health, highlighting the possibility that income not only positively affects people's health through an increase in health investment, as often expected, but could also harm one's health through certain economic mechanisms.

One such economic mechanism is an increase in the consumption of harmful goods or engagement in economic activities that potentially elevate health risks. Consistent with this, a study revealed health deterioration following the arrival of income, as evidenced by an increase in healthcare visits and mortality related to illicit drug use (Dobkin and Puller, 2007). Subsequently, Evans and Moore extended the analysis to encompass a broader spectrum of causes of death, demonstrating that this phenomenon is more universal (Evans and Moore, 2011, 2012). Their studies reveal that the increase in mortality includes deaths due to external causes such as traffic accidents or non-accident-related injuries as well as deaths due to illnesses such as heart disease, heart attack, and stroke. Moreover, Evans and Moore show a parallel monthly cycle in economic activities with mortality patterns, measured by an increase in lottery sales and foot traffic in shopping malls (Evans and Moore, 2012). These studies suggest that economic activities induced by income are detrimental to health, impacting diverse dimensions of well-being.

There are still important unanswered questions about the relationship among income receipt,

[1] Interestingly, empirical evidence does not necessarily support the theoretical expectation, demonstrating that income per se has only limited effects on an individual's physical health and health-related activities, using lottery winnings as a random assignment of positive income shocks (Cesarini et al., 2016; Östling et al., 2020) or tax reform as an exogenous change in wealth (Erixson, 2017).

economic activity, and health. The first and most important question is whether economic activities indeed contribute to health deterioration after income arrival. Thus far, no analyzed data records both daily activities and health conditions at the individual level around the day of income receipt, and as a result, there is no observed direct link between the two. Establishing a connection between activities and the corresponding health changes within a short time frame is a challenging yet crucial task to enhance our understanding of the relationship. The second question is what types of economic activities are more likely to be boosted by income arrival than others. A previous study indicated that shopping, watching movies, and buying lottery tickets increase around income arrival but watching Major League Baseball games and using the subway do not (Evans and Moore, 2012). Examining a comprehensive set of activities based on detailed information about where they occur enhances the understanding of the various pathways between income arrival and health and determines the relative risk of each type of economic activity. The third question is how particular health conditions are related to certain economic activities. Medical literature shows that various activities could elevate the risk of cardiovascular events (Schwartz et al., 2018). Whether and how the relationship extends to other health risks beyond cardiovascular events provides knowledge on a physiological path from economic activities to health.

We address these questions utilizing ambulance transport records. Using ambulance transport data has several advantages. First, it captures nonfatal health changes while being better suited to measuring immediate health changes. Other types of medical utilization are often scheduled in advance and therefore have a slight discrepancy with health changes. Second, the ambulance records encompass detailed information on the location of incidence as well as its severity and diagnosis. The location information is key information in identifying the type of economic activities. In addition, ambulance transport provides a disease code for each case, aiding in linking economic activities with specific health problems. Third, the ambulance transport data records the exact time when emergency medical services are called, providing insights into how people's behavior changes not only over the course of a month but also throughout the day.

We hypothesize that income arrival increases with ambulance transports reflecting health deterioration, and that the increase is generated by increased economic activities upon income arrival. Previous studies use various types of income shocks, including regular payment and one-time payment, to investigate short-term responses to income arrival.[2] We use pension payment as

[2]These include social security payments, government transfers, salary payments, tax rebates, and dividend payments.

an income shock following previous studies (Evans and Moore, 2011; Gross et al., 2022).[3] The Japanese setting confers benefits for analyzing the impact of income receipt on health for at least two reasons. First, pension benefits in Japan are, in principle, distributed on the 15th every two months. This allows for a comparison of within-month cycles in ambulance transport between the months of payment and non-payment, controlling for some day-specific effects within a month. While within-month cycles in mortality studies often focus on the first day of the month as a day of payment, changes in economic activities could be driven by the "beginning of month effect" or nonincome factors that occur around the first day. In this study, we aim to provide evidence that health deterioration upon income arrival occurs, controlling for a specific day effect within a given month. Some previous studies have addressed this issue utilizing differences in the timing of income receipt to identify the effect. For example, one study uses the different timing of salary payment in a month (Andersson et al., 2015). Another study uses the difference in the timing of economic stimulus payments in 2008, which are determined randomly by people's social security numbers (Gross et al., 2014).

Second, pension payments represent a large share of elderly people's income, and there are no significant income shocks on other days for the majority of these individuals. Furthermore, the pension system is compulsory and covers all elderly individuals in the country with no opt-out options.

In addition to the pension system, the Japanese setting offers two additional merits to the analysis in the context of the response to income shocks. First, in Japan's emergency medical services, calling for and using an ambulance is free of charge, helping disentangle the *health* effect from the *income* effect in the observed change in ambulance transport. There are potentially two pathways to explain an increase in healthcare utilization upon income arrival: immediate health deterioration (the *health* effect) and a service utilization increase due to a relaxation of liquidity constraints (the *income* effect) (Gross et al., 2014, 2022). The use of healthcare with costs prevents us from distinguishing between these two effects, whereas a setting with no costs for emergency medical services allows us to concentrate solely on the direct impact of health changes, independent of income.

Another noteworthy aspect of the Japanese setting is the deep dependence on cash in transac-

[3] Evans and Moore (2011) examine the effect of income receipt on mortality using social security payment as an income shock. Gross et al. (2022) examine the effect of gaining liquidity on prescription drug purchases using within-month variation in social security payment.

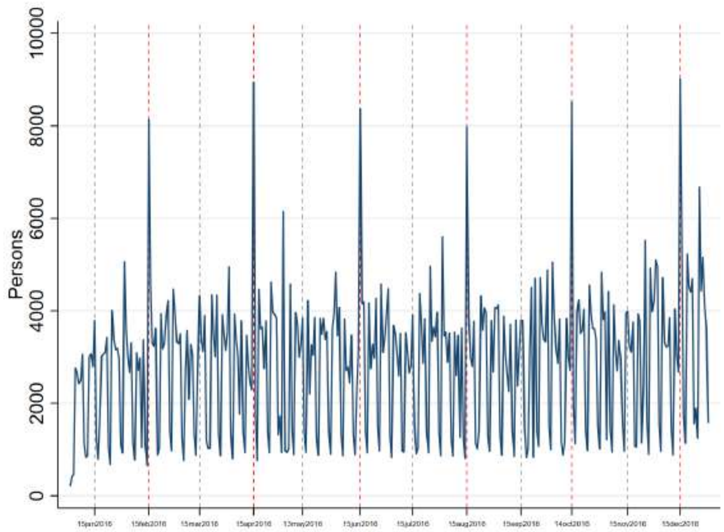
tions. The literature shows that one of the major reasons for health changes is stimulated economic activity through improved liquidity (Evans and Moore, 2012). This suggests that the health effects associated with receiving income may be more noticeable among individuals who lack the means to effectively smooth their consumption patterns. Japan has a deeply ingrained reliance on cash as a mode of payment, especially among the elderly population, who may not be familiar with electronic payment methods.[4] Consequently, the use of credit cards, a typical device for consumption smoothing, is less prevalent than in other countries.

Related to this point, to illustrate the motivation of our study, Figure 1 shows the number of persons who withdraw cash from an ATM provided by Mizuho Bank Inc., one of the three largest commercial banks in Japan, for those aged 75 years old in 2016. Red dashed vertical lines show the pension payday, which is, in principle, the 15th of even-numbered months, and dark gray dashed lines show a corresponding date in odd-numbered months. ATM cash withdrawal spikes only on the day of pension payment that comes every other month, and no such hike is observed for the corresponding day in odd-numbered months, or on any other days. The figure suggests that pension payments are made promptly on the scheduled day without any expeditions or delays and that a significant number of elderly individuals eligible for pensions tend to withdraw cash on the specific day of their pension payment. The figure shows only one age group for one year, but the pattern is consistent across age groups and years (Appendix Figure B1).

This study contributes to four key areas of literature. First, as noted above, it contributes to the short-term effect of income on health by connecting income receipts with health changes following economic activities. Second, our result has an implication regarding excess sensitivity in consumption. Previous studies show that people do not always smooth their consumption and are often responsive to the arrival of anticipated income changes. We show that such a change occurs in the broader range of consumption and it causes a negative impact on health, an important aspect of welfare. Third, recent studies show the unintended effect of government transfers on various welfare outcomes, such as education and crime (Carr and Packham, 2019; Bond et al., 2022). This study contributes to the literature, indicating that income transfer elevates health risks among elderly individuals. Fourth, there is a series of studies on the optimal payment cycle (LaPoint and Sakabe, 2022), and this study has implications for the literature by demonstrating

[4]The ratio of currency circulation to GDP in Japan was slightly above 20% in 2017, nearly double that of the Eurozone and India, more than double that of the US and Korea, and four times higher than Canada, the UK, and Sweden (Sakamaki, 2019). Yoshizawa et al. (2021) argue that a greater preference for cash among elderly individuals is the reason for the high circulation of banknotes in Japan.

Figure 1: Daily number of individuals aged 75 years who withdraw cash, 2016




*Notes*: The figure shows the daily number of individuals who withdrew cash aged 75 years in 2016, obtained from a large commercial bank in Japan. The red dashed lines show the pension payday, typically on the 15th of even-numbered months, and the gray dashed line shows the corresponding day in odd-numbered months.

that the payment cycle affects one's welfare not only through consumption but also health status.

# 2 Institutional Background

## 2.1 The Japanese National Pension System

This section briefly introduces Japan's public pension system (Japanese National Pension System). The public pension system is compulsory, and there is almost no opt-out option. The public pension system was established in 1961, and since then nearly all elderly individuals in Japan have received pension payments under the public system.[5] The system consists of two tiers. The first tier is the basic pension scheme (*Rorei kiso nenkin*). The basic pension requires a minimum of ten years of contributions, and a full pension requires 40 years of contributions. The benefits are adjusted proportionally for shorter contribution periods. The contribution is flat-rate, and the payment is also fixed across individuals. In 2020, the full annual basic pension benefit was 781,700 Japanese yen (5,390 US dollars). The second tier is built on top of the first tier and is salary-based, and those who were employed receive additional payments (*Rorei kosei nenkin*). For the second tier,

[5]There is also a voluntary pension scheme provided by employers in addition to the public pension system. In 2019, 31% of those aged 25 to 64 years were eligible for the employer-provided pension.

the contribution is earning-related and the amount of pension payment is also earning-dependent. The earning-related pension benefit is based on the remuneration and the length of the period that an individual enrolls in (that is, how long they were employed). Most importantly, in both the first and second tiers, the payments are combined and paid on the same day, and the distinction between the first and second tiers does not matter for pensioners who receive both.

For the basic pension, pension payment, in principle, starts in the next month in which one reaches 65 years of age.[6] For the second tier, pensionable age depends on cohorts and gender because the pensionable age is gradually shifting from 60 years old to 65 years old.[7] However, all the cohorts become eligible to receive a pension no later than 65 years of age. The pension system allows some flexibility for individuals to receive it earlier or later than at 65 years of age, and the payment amount is adjusted accordingly. Those who chose to receive their pension before their pensionable age represent 26.1% for the first-tier basic scheme and 0.5% for the second-tier salary-based pension scheme in 2020. Together with cohorts who become eligible after 65 years of age to receive a pension from the second tier, a non-negligible number of individuals start receiving the pension between 60 and 65 years of age. In contrast, those who choose to receive it later than 65 years of age represent only 1.8% and 1.0% for the first and second tiers in 2020, indicating that almost all of those aged 65 years or above receive pension income. Thus, our analysis focuses on the elderly aged 65 years or above.[8] Our main analysis is an intention-to-treat analysis, although the probability of being treated is nearly 100%. The average monthly pension income including both first and second tiers if applicable for those 65 years old or above is 123,000 Japanese yen (848 US dollars) in 2019.

Since 1995, the pension payday has been set to be the 15th of even-numbered months, and individuals receive the pension for the preceding two months. For example, pensions for December and January are paid in February. If the 15th is a Saturday or Sunday, the payment is delivered on the Friday immediately preceding the 15th. There are no holidays on or near pension paydays during the study period and thus no change in pension paydays associated with holidays.

[6]Specifically, for those who were born on the first day of a month, the pension starts in the birth month. For all others, the pension starts in the next month

[7]Specifically, the pensionable age is 60 for males born before April 1, 1953, and for females born before April 1, 1958. For males born after April 1, 1961, and for females after April 1, 1966, the pensionable age is 65. Cohorts born between these ranges gradually experience a delay in pensionable age. As those who were born in 1953 were 66 years old in 2019, which is the most recent year of our study, the pensionable age is 60 for the majority of individuals in our analysis.

[8]As we explain later, we also set the upper limit because, based on our hypothesis, we want to focus on relatively active age groups.

## 2.2 Emergency medical services

As in many developed countries, emergency medical services provide out-of-hospital acute care and transport to definitive care in hospitals. These services are public and operated by the fire department, which is run by either a municipality or a group of municipalities. As of 2020, there were 723 fire departments with 1,714 fire stations in the country (Fire and Disaster Management Agency, 2020). Emergency medical services cover 99.9% of the population, and ambulances, located in local fire departments, are typically dispatched from the closest fire department to the patient. In case of a medical emergency, people dial 119 to request assistance. Note that calling and using an ambulance does not incur any cost for patients. Given higher health risk among the elderly population, individuals aged 65 or above accounted for 62.3% of all transports in 2020. There are 6,579 ambulance cars in Japan, which corresponds to 5.3 per 100,000 population.

# 3 Methods

## 3.1 Empirical model

We analyze the health response to income arrival using the Japanese National Pension System for the elderly population. To analyze the relationship between pension payment and ambulance transport, we construct "synthetic" months following previous literature (Stephens, 2003; Evans and Moore, 2012). The synthetic month begins 12 days prior to the 15th (or the 14th or 13th if the 15th is Saturday or Sunday) and ends 12 days after the payment, resulting in 25 days per synthetic month. The payment is made every other month, but the variable of interest, *Payday(d)*, is defined every month following the rule above. This means that the variable *Payday(0)* indicates not only the day of pension payment but also the corresponding day of nonpayment months. Our identification relies on the difference between payment (treatment) and nonpayment (control) months on *Payday(d)* of a month. This allows us to control for specific date effects such as busier business days on certain days of a month.[9] The idea of comparing payment and nonpayment months is used by Stephens and Unayama (2011) in assessing the impact of anticipated pension payments on the consumption of households using the Japanese data. Their study uses variations across months, and we further rely on daily fluctuations within a month as a source of variation.

[9]For example, dates that are multiples of five are common for business transactions in Japan.

In the main analysis, we use the following equation:

$$ln(Y_{dmy}) = \alpha + \sum_{d=-12, d\neq-3}^{12} \beta_d\{Payday(d) \times Paymonth(m)\}$$
$$+ \sum_{j=1}^{6} \gamma_j Weekday(j)_{dmy} + \phi Holiday_{dmy} + \mu_m + \nu_y + \varepsilon_{dmy}, \quad (1)$$

where $Y_{dmy}$ shows the number of ambulance transports of $d$-th day from the payday of month $m$ in year $y$.[10] $Payday(d)$ is an indicator variable that takes value one if the day is the $d$-th day from the payday and 0 otherwise, with $-12 \leq d \leq 12$. $Payday(0)$ thus indicates the 15th of each month or one or two days before the 15th if the 15th is Saturday or Sunday. $Paymonth(m)$ takes value one if the month is February, April, June, August, October, or December, zero otherwise. We set three days before the payday as the reference day in the main analysis and use an alternative day of reference, one day before the payday, in the robustness check. Our coefficient of interest is $\beta_d$ for each $d$, and it expresses the difference between payment and nonpayment months in the relative increase in the number of ambulance transports on the $d$-th day compared to the reference day. $Weekday(j)$ is a dummy variable for different weekdays and set to 1 for Monday and 6 for Saturday where Sunday is the reference day. $Holiday$ is an indicator variables that indicate national holidays as well as New Year days that consist of New Year's Eve and January 1st to 3rd.[11] $\mu_m$ is a month fixed effect, and $\nu_y$ is a year fixed effect. As a robustness check, we allow for greater flexibility, including year-month fixed effects ($\omega_{ym}$). We use clustered standard errors within a synthetic month. The source of variation comes from the daily fluctuation of ambulance cases, and our identification further relies on between-month variation. Specifically, we compare outcomes on the payday and three days before the payday as the reference day, and then compare the difference between payment and nonpayment months, conditional on day-of-week, holiday effects, month effects, and year effects. In some of the analysis, we obtain five-day average of the impact. In these analyses, we prepare four groups each of which consists of five days ($-10 \leq d \leq -6; -5 \leq d \leq -1; 0 \leq d \leq 4$; and $5 \leq d \leq 9$). Then, we apply the same analysis as Equation (1) with the preceding group (i.e., $-5 \leq d \leq -1$) as the reference group in the analysis. The control variables include month and year fixed effects but exclude day-level variables.

[10] Since payday is around the 15th, the synthetic month aligns with the calendar month. Thus, we use calendar months for fixed effects.

[11] Japan's largest holiday is the New Year period, during which many people take days off from New Year's Eve until January 3rd, with only January 1st being the official national holiday.

In addition to analyzing data at the daily level, we explore the evolution of changes in transport *within* the day of pension payment compared with the reference day to determine what time of the day transport increases. In the analysis, the sample is limited to *Payday(0)* (i.e., $d = 0$) and the reference day (i.e., $d = -3$), and we employ the difference-in-difference approach with the same spirit as in Equation (1) with payment and nonpayment months as the treatment and control groups:

$$ln(Y_{dmy}) = \alpha + \beta\{Payday(0) \times Paymonth(m)\} + \sum_{j=1}^{6} \gamma_j Weekday(j)_{dmy} + \phi Holiday_{dmy} + \mu_m + \nu_y + \varepsilon_{dmy}, \quad (2)$$

where $Y_{dmy}$ shows the number of ambulance counts in one of the four-hour intervals of day $d$ of the synthetic month $m$ in year $y$. $Payday(0)$ is an indicator variable that takes value one if the day is the 15th (or 13 or 14 if the 15th is Saturday or Sunday) and 0 if it is the reference day. As in Equation (1), $Paymonth(m)$ takes value one if the month is an even-numbered month, zero otherwise. We set six time intervals (0 am to 4 am, 4 am to 8 am, 8 am to 12 pm, 12 pm to 4 pm, 4 pm to 8 pm, and 8 pm to 12 pm), and we conducted six regressions and report $\beta$ for each interval. Our coefficient of interest is $\beta$, which shows a difference in the change in the number of ambulance transports on the pension payday from the reference day.

### 3.2 Ambulance transport data

**Data structure.** Our ambulance transport data are based on individual ambulance transport cases in Japan between 2007 and 2019 and is provided by the Ministry of Internal Affairs and Communications for research purposes.[12] Until 2015, the provided data covered all cases nationwide except for those completed by the Tokyo Fire Department, which corresponds to the entire Tokyo Prefecture except for Inagi-city and island municipalities that operate their own fire departments. Starting in 2016, the dataset covers the entire county (see Appendix Table A1). The data record information on basic patient attributes such as age and sex, severity of condition, and cause of incidence, as well as transport details including the time of emergency calls and location of the incidence by category. Since 2015, additional information has been provided regarding location

[12] The data is called the "Number of Transported Persons Data *(Kyukyu-hansou jininsu deita)*" and is available only upon application for research purposes. Our application was approved on September 9, 2021.

and physical condition.

**Location.** One of the key variables for our analysis is the location of the incidence. Location is provided in five major categories: home, public space, road, workplace, and other. Furthermore, starting in 2015, detailed codes became available for specifying the location of the incidence. This detailed information breaks down public space, one of the major categories, into 27 subcategories. In the analysis, we aggregate the 27 categories based on the similarity of activities to produce the following nine categories: movie theater or museum; restaurant or bar; place of amusement[13]; department store or supermarket; hospital or nursing home; school; station or airport; hotel; and other. The correspondence between the four major categories and nine subcategories of the public space used in our analysis is depicted in Figure 2a. The examples of locations for each category is found in Appendix Table A2.

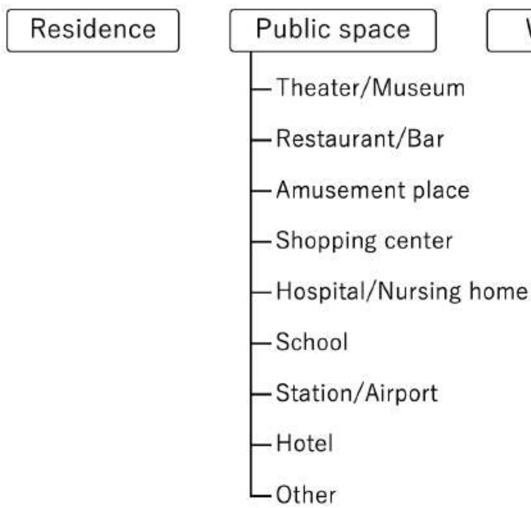
**Incidence type.** The cause of incidence, or incidence type, is categorized into the following 12 categories: fire, natural disaster, water-related accident, traffic accident, labor-related accident, sports and exercise, injury, violence, self-harm, illness, hospital transport, and other. Our primary focus is traffic accidents, injuries, and illnesses, which are considered the main causes related to economic activities, and we therefore aggregate all other categories as "other causes". The dataset also includes a diagnosis for illness given by a physician after 2015. The diagnosis for illness category is categorized into the following ten groups defined by the emergency medical service department: cerebrovascular diseases; heart diseases; digestive diseases; respiratory diseases; mental illness or alcohol- or substance-related conditions; diseases related to the nervous system; cancer; unknown or cannot be classified; and other. The ten groups are defined based on the ICD-10 codes, and the correspondence between the ICD-10 classification and the 10 disease categories by emergency medical service department is found in Appendix Table A2. The correspondence between the major categories and 10 subcategories of diagnosis used in our analysis is depicted in Figure 2b.

**Other information.** Another important piece of information is health condition. Throughout the period, the severity of health conditions determined by the first physician who examines the patient at the hospital is recorded. Severity is classified into five levels: dead, fatal, serious, severe,

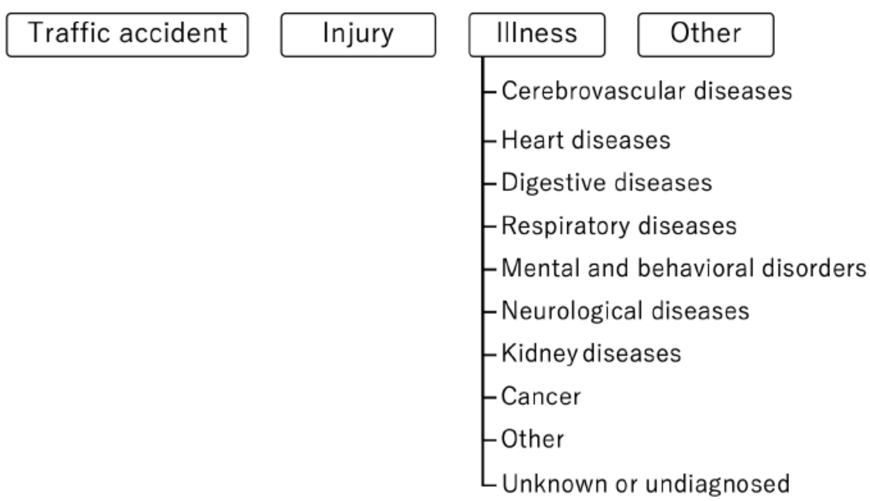
[13]This includes the establishment of *pachinko*, a prevalent form of gambling, wherein prizes earned from games are exchanged for cash

Figure 2: Major categories and subcategories for incidence location and type

(a) Incidence location




(b) Incidence type



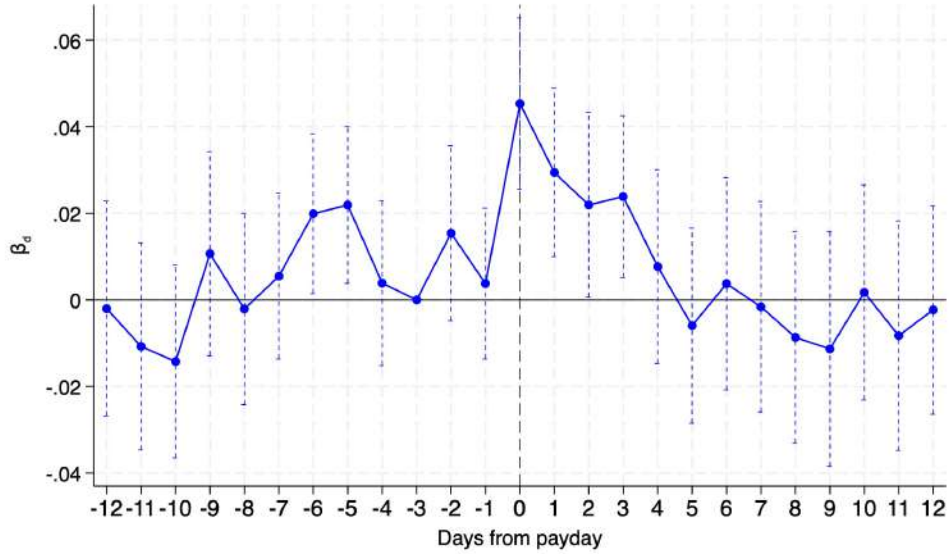

*Notes*: The figure illustrates the correspondence of major categories for incidence location and type and subcategories. The major categories, enclosed in a square box, include subcategories for public space as seen in Panel (a) and illness as seen in Panel (b). The examples of each location category is provided in the Appendix Table A2.

and mild. Mild refers to a condition that does not require hospitalization. Severe refers to a condition that requires hospitalization for less than three weeks. Serious refers to a condition that requires hospitalization for three or more weeks. Finally, a fatal condition is a life-threatening condition.

In this analysis, we concentrate on individuals aged 65 to 79, as they are typically more active and, consequently, more likely to respond to income arrival through economic activities. Appendix Figure B2 shows the ambulance transport cases of those aged 65 to 79 in 2016. We observe an increasing trend over time in the number of transport cases partly due to an increasing population of elderly persons. There is seasonality according to which transports increase in winter and the middle of summer, while an association with pension payment is not clearly observed. In particular, unlike the record of cash withdrawals in Figure 1, we do not observe a clear spike on the pension payday in Panel (b). We will thus perform statistical analyses, controlling for holiday effects, day-of-the-week effects, and month and year fixed effects. Appendix Table A3 shows summary statistics of the key variables for the original dataset including all age groups. Among them, one-quarter of all of the transports falls in the age group of interest for our analysis, and they are shown in Appendix Table A4. We aggregate the case-level data to generate ambulance transport counts at the daily level. The summary statistics for the daily-level data used for our analysis is presented in Appendix Table A5. We have a total of 3,900 observations of 25 days in a synthetic month $\times$ 12 months $\times$ 13 years for the entire dataset. Among these observations, 1,500 after 2015 contain detailed information regarding public space and illness.

We additionally examine the surge in ambulance transports on the specific day of pension payment by analyzing recorded timestamps of what time the emergency call is made. To compare the number of ambulance calls for each four-hour slot on the payday between payment and nonpayment months, we aggregate the number of calls for 4 hours starting at 12 am on the payday until 12 am on the next day. Then, we statistically analyze the data as stated in Section 3.1.

Figure 3: Impact of pension payday on ambulance transport




*Notes*: This figure shows the coefficient estimates of $\beta_d$, where $d = \{-12, -11, ..., -1, 0, 1, ..., 11, 12\}$ from Equation (1) using all the ambulance transport data between 2007 and 2019. The number of observations is 3,900. The dotted bar shows the 95 percent confidence interval. $d = 0$ shows the payday. The coefficient estimates show the difference in the relative increase in ambulance transport cases compared to the reference day, three days before the payday, between payment months and nonpayment months.

# 4 Results

## 4.1 The impact of pension payment on ambulance transport

To understand how ambulance transport pattern changes following a payday, we plot $\beta_d$ from Equation (1) in Figure 3. The number of transport cases does not show any pretrend during the two weeks before the payday, suggesting that payment and nonpayment months are not systematically different, conditional on daily characteristics such as day of week or seasonality. The difference in ambulance transport sharply increases on the day of pension payment compared to the three days before the payday, and the magnitude is 4.5%. The mean number of transports is approximately 3,200, and the increase corresponds to approximately 150 cases per day. The increase in the transports persisted for four days after the payment with a lesser magnitude on the days following the payday and quickly vanished after that. The increase in ambulance transport lasts only for a short period of time. The total impact over the four days is 12.1% ($p < 0.001$).

The spontaneous and very short-term effect of an increase is consistent with Andersson et al. (2015), who find an impact on mortality only on the day of payment but contrasts with that of

Evans and Moore (2011), who show the impact persisted for several days. Andersson et al. argue that the difference is likely due to variations in payment methods. Specifically, Swedish public sector employees, studied by Andersson et al. (2015), received payments through direct deposit, while social security payments in the study by Evans and Moore (2011) were made via physical checks at the time of the study, which takes several days to deposit and cash it. Our findings, which are consistent with the Swedish data, further support this argument, as pension payments in Japan are made through direct deposit.

Appendix Figure B3 shows a breakdown by payment (treatment) and nonpayment (control) months. The figure indicates that the increase on the payday is driven by a change in payment months and is not observed in nonpayment months. If the increase is driven by factors other than pension payment and instead reflects a specific date effect within a month, we should observe an increase in nonpayment months. However, the coefficient remains at approximately zero throughout the synthetic month, indicating that no such effects exist.

The increase in transports may merely reflect a shift from later in payment cycles, often called the "harvest effect". To test whether the increase is offset by a decrease later in the same payment cycle, we analyze a payment cycle that consists of two synthetic months. If an increase in patients is a shift from the rest of the days until the next payday, we would not observe a total increase in the number of transports in two synthetic months in this analysis. As we do not take a difference between payment and nonpayment months, the regression coefficient of Day $d$ shows a difference in ambulance transports from the reference day in this analysis. Then, we test the null hypothesis that the sum of all the coefficients of a binary variable to indicate Day $d$ over two synthetic months is equal to zero. If the "harvest effect" exists, the increase on the payday would be offset by a decrease on other days of the rest of the payment cycle, and the sum of all the coefficients of the binaries, which shows the total change in a payment cycle, becomes zero. The total increase in the two synthetic months in ambulance transport is 85% ($p = 0.07$). Although the increase is not statistically significantly different from zero at the conventional level, the total effect shows a positive sign with a greater magnitude than the sum of the first four days 12.1%, which is discussed in relation to Figure 3. The result suggests that the increase is not merely a shift in the timing of emergency service utilization but rather an increase in ambulance transport after the pension payday.

## 4.2 Incidence location and economic activities

The subsequent inquiry pertains to what type of economic activities individuals typically engage in upon receiving income. To address this question, we analyze the impact by the location of incidence, and the results are found in Figure 4. Figure 4a illustrates the impact of the payday by the four major location categories. In the left panel displaying the payday coefficient ($\beta_0$), the largest impact is found in transports from roads with a 14.4% increase, followed by public spaces with 7.2%. The increase is consistent with the hypothesis that people increase their activities. There are not a large number of transports through the synthetic month from the workplace (see Appendix Tables A4 and A5), resulting in a large confidence interval for the workplace coefficient. The right panel shows the five-day average effect starting from a payday. The rise in transportation is less pronounced than the notable increase observed on paydays for roads and public spaces. This indicates that the impact diminishes in the first five days following payment, consistent with the observations from the main results depicted in Figure 3. The full results for $\beta_d(-12 \leq d \leq 12)$ are found in Appendix Figure B4.

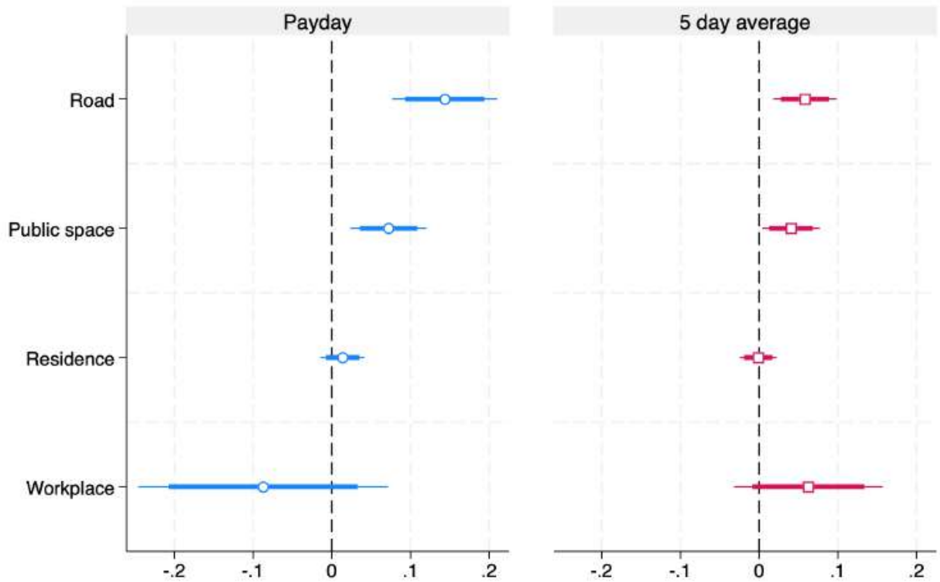
These results indicate that people are more likely to have health problems in places outside their homes on and following the pension payday. One may think that this increase in ambulance transports in public spaces and roads might reflect a change in where people are located and thus a shift in incidence location, rather than health deterioration triggered by income receipt. However, we can exclude this possibility for the following two reasons. First, we observe an overall increase in transport on the day of pension payment in the main analysis in Figure 3. Second, we do not find a decrease in transport from residences, which is most likely the place where incidence would occur in the absence of pension payment, to offset the observed increase for roads and public spaces.

Figure 4b shows the further breakdown of the public space category into the nine subcategories, which provides useful information on the activities people engaged in upon income arrival. The most substantial surge is observed in transports from amusement arcades, with one popular venue among adults in Japan being referred to as *pachinko parlors*. In Japan, gambling is not legally permitted except for the following four public gambling: horse racing, bicycle racing, motorboat racing, and auto racing. However, pachinko parlors, a form of gambling establishment, are very common, where individuals participate in machine-based games for nonmonetary rewards, which can later be exchanged for cash.[14] Moreover, note that pachinko parlors exclusively accept cash as

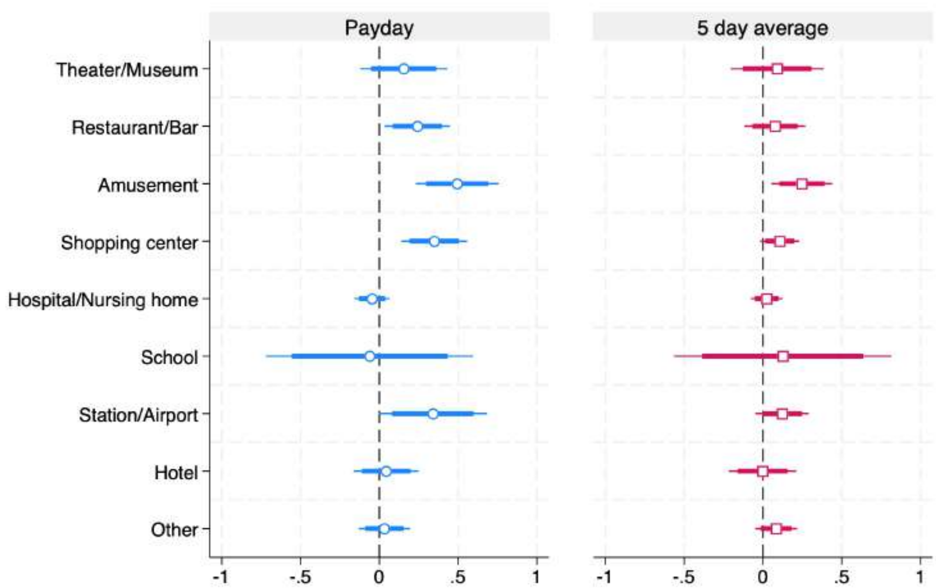
[14] There were 7,665 pachinko parlors in Japan in 2022.

Figure 4: Impact of income receipt on ambulance transport on the payday and five-day average of the impact by incidence location

(a) Large category




(b) Public space




*Notes*: This figure shows the coefficient plot of $\beta_0$ in the left panel and the five-day average in the right panel using all the ambulance transport data between 2007 and 2019 for Panel (a) and between 2015 and 2019 for Panel (b). For Panel (a), the number of observations is 3,900 for the left panel and 624 for the right panel. In Panel (b), the number of observations is 1,500 for the left panel and 240 for the right panel. The thin bar shows the 99% confidence interval and the thick bar shows the 95% confidence interval. The numbers show the difference in the relative increase from the reference day in ambulance transport cases between payment months and nonpayment months. The reference day is three days before the payday for the left panel and the preceding five-day block before the payday for the right panel. The examples of each location category are presented in Appendix Table A2.

the mode of payment, which could contribute to a sharp response on the payday due to liquidity relaxation. The magnitude of the increase on the payday is substantial and 49.3%. The second-largest increase is found in shopping places such as department stores and supermarkets with a 34.8% increase, followed by stations and airports with a 33.9% increase, and restaurants and bars with a 24.1% increase. In contrast, there was no notable increase observed in transport from hospitals or nursing homes, where we would not expect an increase on paydays.

Persistence in the impact exhibits variation across locations. Appendix Figure B5 shows the complete result for amusement arcades including 12 days before and after the payday. There is a distinct pattern in ambulance transports on pension paydays, characterized by a notable surge on the payday followed by a gradual decline over the subsequent days. In the right panel of Figure 4b, the average impact over the first five days is most pronounced in amusement arcades. Examining the cumulative effect, there is a 110% increase over the first three days and a 147% increase over the five days. In comparison, the corresponding increases are 44.5% and 57.0% for shopping centers and 43.0% and 53.3% for restaurants and bars. Thus, the impact in amusement arcades including pachinko parlors is not only distinct in magnitude but also in its duration of persistence.

These results indicate that economic activities are stimulated upon the receipt of income, with amusement and gambling, shopping, and dining out being the primary activities that respond to the arrival of income and have adverse health effects.

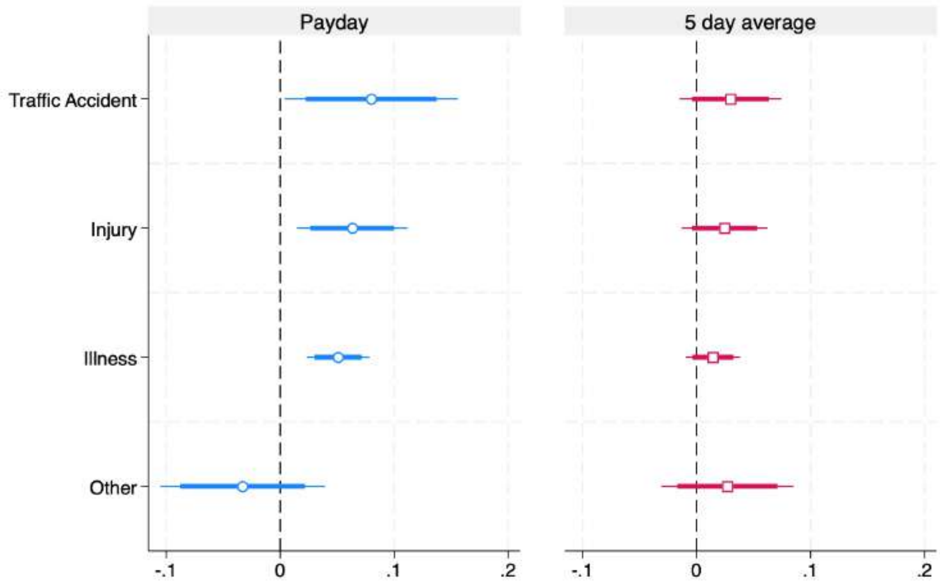
## 4.3 Health changes

The next question concerns the nature of health changes that occurred. Figure 5 shows the breakdown by incidence type and by diagnosis. Figure 5a shows the impact by incidence type. The increase in transport was a product of external causes such as traffic accidents and injuries as well as illnesses. This is consistent with previous findings for mortality that find an increase in mortality due to illnesses including cardiovascular events (Evans and Moore, 2011; Andersson et al., 2015). Specifically, traffic accidents increased by 7.9%, followed by 6.3%, and 5.1% for injuries and illnesses, respectively. By contrast, no such increase is found in transport due to other reasons, which include fire, natural disasters, and work-related health hazards. Appendix Figure B6 shows the full results.

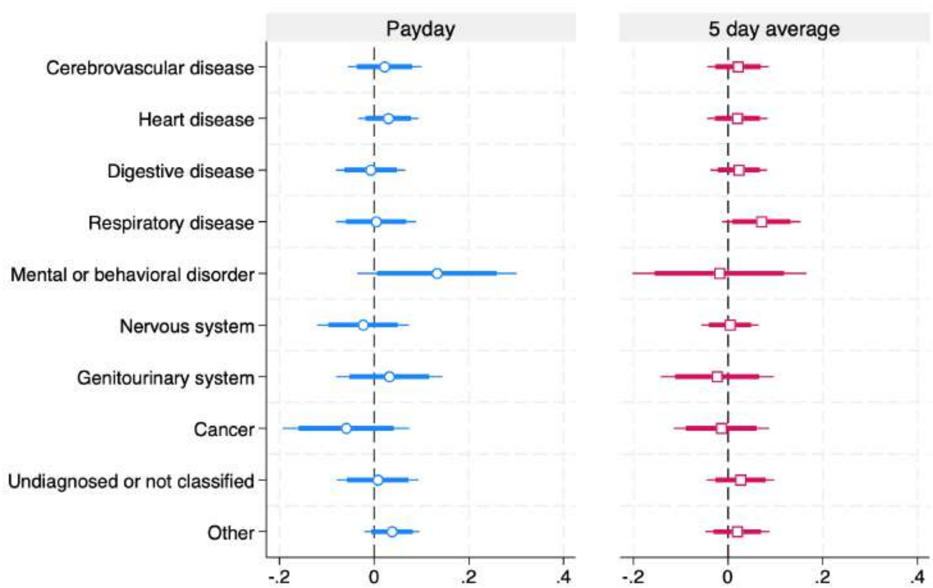
We further examine the impact by diagnosis that is given for illnesses in Figure 5b. Transports due to mental and behavioral disorders, including alcohol-related behavioral disorders, show an

Figure 5: Impact of income receipt on ambulance transport on the payday and five-day average of the impact by incidence type and diagnosis

(a) Incidence type




(b) Diagnosis for illness




*Notes*: This figure shows the coefficient plot of $\beta_0$ in the left panel and the five-day average in the right panel using all the ambulance transport data between 2007 and 2019 for Panel (a) and between 2015 and 2019 for Panel (b). For Panel (a), the number of observations is 3,900 for the left panel and 624 for the right panel. For Panel (b), the number of observations is 1,500 for the left panel and 240 for the right panel. The thin bar shows the 99% confidence interval, and the thick bar shows the 95% confidence interval. The numbers show the difference in the relative increase from the reference day in ambulance transport cases between payment months and nonpayment months. The reference day is three days before the payday and the preceding five-day block before the payday for the right panel. The definition of each incidence type and diagnosis category is presented in Appendix Table A2.

increase. For some conditions such as cerebrovascular diseases or heart disease, the coefficient of payday is positive but not significant at conventional levels. The full result for mental and behavioral disorders is found in Appendix Figure B7.[15]

Next, we consider a breakdown by location and diagnosis. We focus on four locations under public space where the rise in ambulance transports on pension payday is large. The results are shown in Appendix Figure B8. There is a noteworthy divergence in patient diagnoses across these locations. This suggests that distinct economic activities are associated with different health problems, rather than a simple increase in transport due to higher traffic in specific areas. For example, there are increases in heart disease cases linked to amusement places that are significant at the 5% level, whereas mental and behavioral disorders, including alcohol-related issues, are more prevalent in transport from restaurants and bars. Transport due to injuries from airports and stations also increases. To summarize, activities in amusement arcades tend to increase diseases such as heart disease, drinking and dining increase mental and behavioral disorders, and traveling increases injuries.

## 4.4 Within-day variation

Finally, we examine in detail when the increase occurred at a particular time of day to explore when people change their behavior on payday and if these changes are related to business hours. Figure 6 shows a plot of the number of transport cases of the payday in each 30-minute interval (Figure 6a) and the corresponding figure for the reference day (Figure 6b). In each panel, there are two lines: the blue line is for payment months, and the black line is for nonpayment months. On the payday, as illustrated in Figure 6a, there is no distinction between payment and nonpayment months during midnight and early morning. However, the two lines begin to diverge around 9 am approximately when business hours commence.[16] This gap persists throughout the day, with the margin gradually decreasing in the evening. Notably, such deviation is not observed on the reference day in Figure 6b or for the pension ineligible age group in Appendix Figure B9. The results suggest that elderly individuals start engaging in economic activities after business hours

[15] Figure 5a shows a statistically significant increase in illness on payday, whereas Figure 5b indicates significant impact for a single category, with wider confidence intervals. The difference partly arises from variations in the study period:the former incorporates all data from our study period spanning 2007 to 2019, while the latter only includes data from 2015 to 2019, during which diagnosis information is available.

[16] As the pension payment is made using direct deposit, it is delivered before 8:45 am on the payday. In Japan, banks and many supermarkets open at 9 am. Pachinko parlors usually open between 8 am and 10 am. Department stores typically open at 10 am.

begin.

The results are shown by incidence location and type: for four major location categories in Appendix Figure B10; for amusement arcades in Appendix Figure B11; for incidence type in Appendix Figure B12; and for mental and behavioral disorders in Appendix Figure B13.

The analysis by incidence location in Appendix Figure B10 clearly shows that the increase after 9 am is driven by transports from public spaces and roads, not from the workplace. The figure shows a slight increase in the number of transports from home in the afternoon. Additionally, in Appendix Figure B11, the difference between payment and nonpayment months is pronounced in transports from amusement arcades, as we expected from the main analysis. For the analysis by incidence type in Appendix Figure B12, the difference between payment and nonpayment months is observed in all causes except for others, consistent with the analysis with daily data in Figure 5a. The analysis for mental and behavioral disorders in Appendix Figure B13 is noisy and does not show a clear pattern. However, the increase in transport during the evening is only observed in payment months and not in nonpayment months. This trend is likely caused by payment-related behavior.

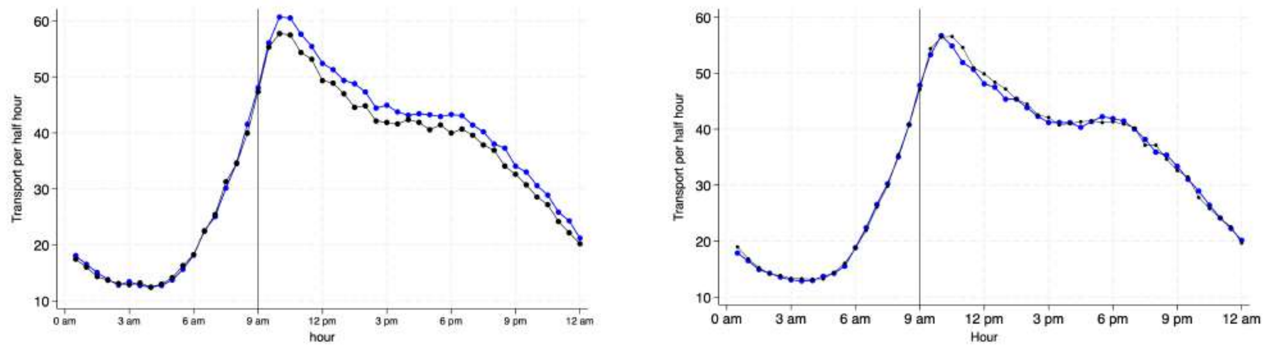
Figure 7 shows the coefficient of the interaction term of *Payday* and the pay-month dummy in Equation (2) to conduct the formal statistical test of whether a change on the payday in the number of transports from a reference day differs between payment months and nonpayment months for all and for age and gender groups. Overall, we confirm a significant increase after 8 am. The regression results by incidence location and type are found in Appendix Figure B14. The difference starting in the morning is significant in transports from public spaces and roads but not from the workplace or residence. We also find a statistically significant increase in injuries and traffic accidents at night.

## 4.5 Heterogeneous impact

Finally, we investigate heterogeneity in the impact of pension payment by gender and age group, severity of condition, and month. As stated in the introduction, we hypothesize that the increase is driven by a rise in economic activities. Therefore, we expect a greater response among those who are relatively younger, and among those in relatively good health conditions, particularly during favorable seasons for going out, such as spring between March and May and fall between September and November. The coefficient of $\beta_0$ is plotted in Figure 8, and the full results are

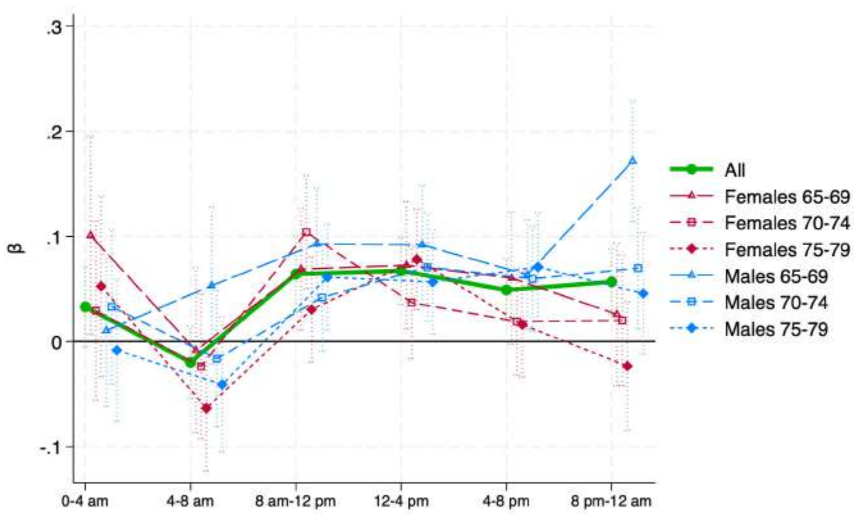
Figure 6: Ambulance transport by half-hour on the payday and reference day

(a) Payday (b) Reference day



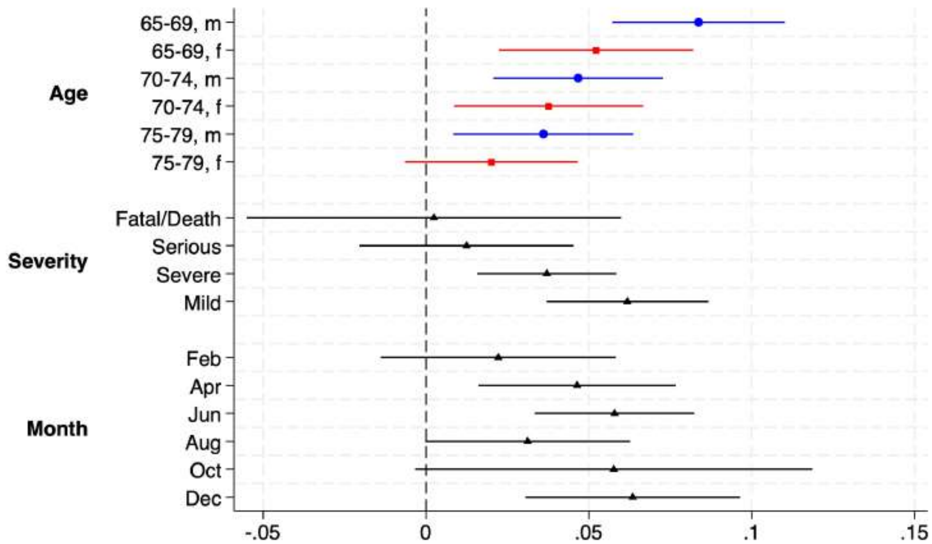

*Notes*: This figure shows the plot of the average number of ambulance transport cases in each 30 minute bin over the sample period, 2007 to 2019. Panel (a) shows the number of cases on the day of pension payment, and Panel (b) shows the trend on the reference day, three days before the payday. In each panel, there are two lines. The blue line shows payment months, and the black line shows nonpayment months.

Figure 7: Increase in ambulance transport on the payday, regression analysis




*Notes*: This figure shows the coefficient plot of $\beta$ from Equation (2) for each four-hour interval. The dotted bar shows the 95 confidence interval. The regressions are performed separately for each of the six intervals. For each analysis, the number of observations is 312. The results are presented for all individuals between 65 and 79 as well as by age and gender.

Figure 8: Heterogeneous impact by age and gender, severity, and month




*Notes*: This figure shows the coefficient plot of $\beta_0$ from Equation (1) using the ambulance transport data between 2007 and 2019. The number is 3,900 for the analysis by age and severity and 2,275 for the analysis by month. The bar shows the 95% confidence interval. The numbers show the difference in the relative increase from the reference day in ambulance transport cases between payment months and nonpayment months. The reference day is three days before the payday. The blue color shows males, and the red color shows females. Three age groups are analyzed: 65-69, 70-74, and 75-79. The definition of severity is presented in Appendix Table A2.

plotted in Appendix Figure B15 for age group and Appendix Figure B16 for severity. In Figure 8, the rise in ambulance transports on the pension payday is most notable among individuals in the youngest age group, specifically those aged 65 to 69 years. The impact diminishes with increasing age for both genders. This pattern across age groups suggests that health shocks are more prevalent among the younger demographic. The effect is greater among males in all groups than females. Additionally, the increase is the greatest for mild conditions and monotonically decreases with severity, and we do not obtain a significant impact for those with fatal conditions, who died, or those with serious conditions. While we lack information on the patients' health conditions before they require emergency medical services, an increase in mild cases could imply that those who fell ill were not in significantly poor health at the time of ambulance transport, indicating an acute change in health status triggered by activities. We observe seasonality in the effect. The interpretation of the results concerning seasonality is not straightforward. Nevertheless, it appears that there are fewer ambulance transports observed during periods of extreme weather such as in February and August.

How ambulance transports change on the payday in all gender-age groups between 65 and 79 is found in Appendix Figure B17. There is a difference in the timing of increases by age and gender. Overall, the impact is more pronounced for men. In younger males, the increase persists until midnight, while for females, the effect begins to diminish after 4 pm.

## 4.6 Mechanism

### 4.6.1 Liquidity

The remaining concerns relate to what contributed to a change in activities on the payday. Regarding the mechanism of the increase, two main reasons could be considered for the rise in ambulance transport from the classical economic model.[17] The first channel involves a relaxation of liquidity constraints. Previous studies indicate that individuals increase consumption on the day of pension payment, and this effect is more pronounced among those with more constrained liquidity. Our results, showing larger jumps in transports from places of amusement—some of which only accept cash—support this rationale.

Although the administrative ambulance record does not include the patient's socioeconomic status and we cannot test this directly, we attempt to examine whether the relaxation of liquidity is likely to drive the result through two analyses. First, we utilize an original survey we conducted to ask about people's behavior and their economic situation in the three days around the pension payday. While our primary analysis relies on comprehensive ambulance transport data encompassing all of Japan, we incorporate insights from the survey to enhance the understanding of the role of the economic factors in the mechanism. The survey spanned three consecutive days surrounding the pension payday (i.e., one day before the payday, the payday, and one day after the payday) in June 2023. We asked 1,000 individuals aged 65 years or older, inquiring about their awareness of the pension payment schedule, their activities on each day, and their overall financial situation. The survey was distributed to the registered individuals via a commercial survey company. We obtained approval from the Internal Review Board at Hosei University (Approved on June 16, 2023, with the approval number 2023S02).

The primary objective of utilizing the survey data is to investigate the difference in the relationship between a pension payment and activities by liquidity status. Specifically, we ask whether individuals used ATMs or banks on each of the three days to examine a change before and after

[17] We will discuss other factors related to behavioral economics in Section 5.

a payment. The reason why we employ ATM use, rather than specific activities such as shopping, is that all economic activities should start with obtaining cash if income receipts increase economic activities. Additionally, we incorporate self-reported step counts for each day into our analysis. Participants were instructed to provide their step counts using an application on their smartphones, smartwatches, or similar devices.

To assess liquidity, we posed two questions. First, we inquired about the economic situation just before the pension payday, offering two response options: whether the pension payment is sufficient to cover living expenses and some money is left, or if the entire pension payment is consumed before the next payday. For those indicating the latter, they were directed to respond to a more detailed question about their economic situation, choosing from five responses: having financial assets but avoiding their use for daily living expenses, attempting to reduce expenses; using some of the assets alongside the pension payment for daily living expenses; lacking financial assets and relying on family support; lacking financial assets and resorting to borrowing money; and lacking financial assets, family support, and borrowing. We classify individuals who lack assets and family support as liquidity-constrained. Specifically, we define those who are liquidity-constrained if they respond with either "lacking financial assets and resorting to borrowing money" or "lacking financial assets, family support, and borrowing"; otherwise, they are considered not liquidity constrained.

To analyze the data, we construct a panel dataset at the participant level with three survey days (i.e., a respondent-survey-day panel). We set one day before the payday as the reference day and compared a change in their activities on the following two days in footstep counts as well as ATM or bank use. In the regression, we control for individual fixed effects. We restrict the analysis to respondents who reported recognizing the dates of pension paydays. Additionally, we identify and treat records with more than 50,000 steps per day as potential misrecordings, and replace them with missing values.

In Table 1, we compare ATM/bank use and footsteps before and after the pension payment based on perceived liquidity constraints. As in previous literature, the number of those who are liquidity constrained is not large, and the vast majority are categorized as those who are not liquidity constrained. The coefficients show an increase in the probability of using an ATM or bank and an increase in footstep counts on the payday and the preceding day compared to one day before the payday.

Table 1: Bank or ATM use and footstep count by perceived liquidity constraint

| | All | Not constrained | Constrained |
|---|---|---|---|
| *Probability of using ATM or bank* | | | |
| Coefficient of *Post* | 0.105*** | 0.100*** | 0.161** |
| | (0.0120) | (0.0124) | (0.0492) |
| Observations | 2640 | 2463 | 177 |
| *Footstep counts* | | | |
| Coefficient of *Post* | 315.4* | 274.3 | 1231.8 |
| | (144.1) | (147.3) | (683.1) |
| Observations | 1354 | 1292 | 62 |

*Notes*: $^{*}p < 0.1;^{**}p < 0.5;^{***}p < 0.01$. The coefficient of *Post* shows the difference in the probability of using an ATM or bank and footstep counts on the day of payment or the following day compared to one day before the payday, based on the survey conducted in June 2023. We control for individual fixed effects. Standard errors are in parentheses. We classify individuals as liquidity constrained if they respond with either "lacking financial assets and resorting to borrowing money" or "lacking financial assets, family support, and borrowing"; otherwise, they are considered not liquidity constrained.

In the results using the full sample, we find that individuals are more inclined to use ATMs or banks on the payday and the following day, compared to one day before the payday. This aligns with the outcomes of our primary analysis. The increase in using ATMs or banks is found among both those who are liquidity constrained and those who are not. However, the difference between the days before and after the payday is more pronounced among those who reported being constrained in their liquidity. Specifically, the probability of using an ATM or bank is higher among the liquidity constrained than those who are not constrained by 6.1 percentage points. The increase in footstep counts is three times higher among those who are constrained compared to those who are not although the coefficients are not statistically significant in either case. These findings provide suggestive evidence that at least some of the observed behavioral response is influenced by individuals who increase consumption upon the arrival of income due to an upsurge in liquidity.

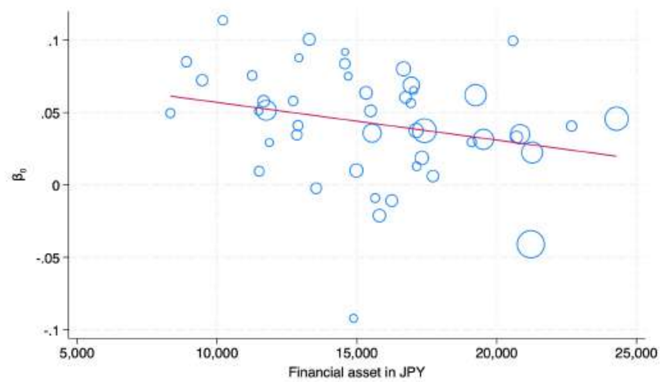
Second, we examine the correlation between the magnitude of the increase in ambulance transports on the payday, obtained from the main analysis, and the individual economic situation, obtained from government statistics, both aggregated at the prefecture level. The magnitude of the increase is measured by $\beta_0$ in Equation (1), where the analysis is conducted separately for each of the 47 prefectures. The coefficients for each prefecture are found in Appendix Figure B18. The economic situation at the prefecture level is measured by the following three variables: financial assets per household with people aged 65 or above; per capita bank savings; and per capita postal savings. While none of the variables directly or perfectly measures the liquidity of the elderly population, we aim to observe the overall tendency using the three supplementary measures of wealth. The health response is considered to be larger in prefectures where a higher proportion of people are liquidity constrained. In Figure 9, there are negative correlations between the effect size of the response on the payday and all the economic variables with degrees varying with the measures. The correlation coefficients are $-0.25$ ($p = 0.09$) for financial assets per household with people aged 65 or above; $-0.46$ ($p = 0.001$) for per capita bank savings; and $-0.46$ ($p = 0.001$) for per capita postal savings. Since the results are not evaluated at the individual level and this is not a causal analysis, we cannot dismiss the possibility of unobserved factors influencing the relationship between the two variables. Nevertheless, at the prefecture level, a greater degree of liquidity constraint is associated with a greater increase in ambulance transport on payday, providing suggestive evidence of liquidity constraint as a reason for an increase.

#### 4.6.2 Supply-side factors

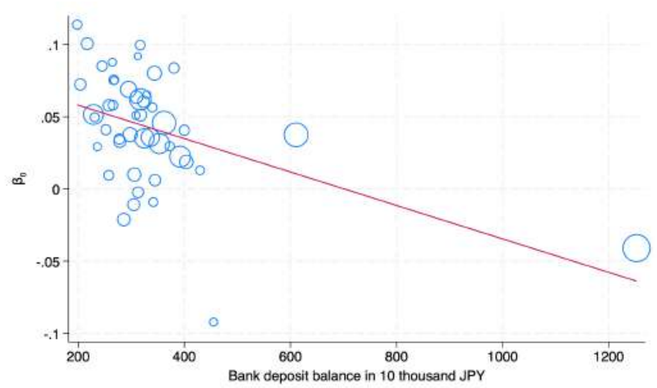
The second channel involves supply-side factors. Given that pension paydays are common among the elderly population, suppliers may adjust prices through sales or other means to attract more customers or boost their revenue. While we are unable to directly test this hypothesis, we believe that it is unlikely to play a significant role in our results. Appendix Figure B9 shows the results from Equation (1) for those 55-59 years old, who are not eligible for a pension. The increase on the payday is not observed among those aged 55 to 59 years, suggesting that the increase is not driven by common factors across age groups. Furthermore, our triple difference analysis, where the additional difference comes from age groups (those aged 55 to 59 years and those aged 65 to 79 years) in Appendix Figure B19 reveals that the magnitude of the increase is approximately the same when compared with the main results in Figure 3. These findings suggest that the response is evident only among those eligible for a pension. Since price discounts are not restricted by the age of consumers, the increased ambulance transport is most likely driven by demand-side factors. This is consistent with a report of non-adjustment of prices by retailers based on predictable demand patterns for government benefits in the US (Goldin et al., 2022).

Figure 9: Correlation between the effect size and wealth at the prefecture level

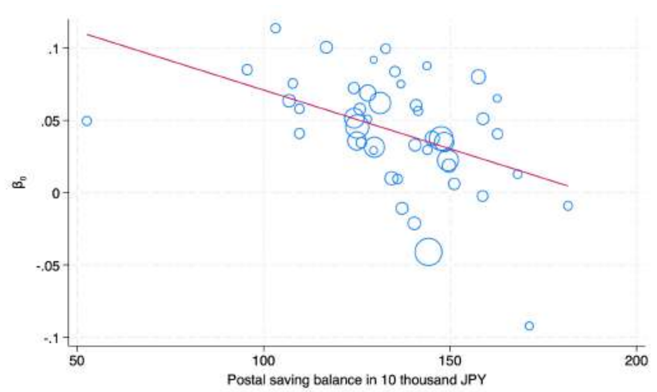
(a) Assets per household with those 65+




(b) Per capita bank deposits




(c) Per capita postal savings




*Notes*: This figure shows the correlation between the $\beta_0$ coefficients estimated for each of the 47 prefectures using Equation (1) and three different measures of wealth, which approximate liquidity. The three measures are financial assets per household with people aged 65 or above; per capita bank savings; and per capita postal savings. The correlation coefficients are $-0.25$ ($p = 0.09$) for financial assets per household with people aged 65 or above; $-0.46$ ($p = 0.001$) for per capita bank savings; and $-0.46$ ($p = 0.001$) for per capita postal savings. All the economic data are obtained from "Statistical observations of prefectures" reported by the Statistics Bureau of Japan. The size of the circles shows the population aged 65 years or above. The red line shows a linear fit.

### 4.7 Robustness check

We conduct two robustness checks to examine the sensitivity of our results. First, we use a different reference day. In the main analysis, we set three days before the payday as a reference day, and we use one day before the payday as a reference day in the robustness check. Second, we use fixed effects for a specific year and month that allow for greater flexibility in the control.

Appendix C shows the set of main results from the analysis with one day before payday as the reference day. Appendix D shows the main results with a different specification with year-month fixed effects. In both analyses, the overall results are consistent with the main analysis.

## 5 Discussion

Our analysis bridged the gap between income arrival, economic activities, and health, identifying certain economic activities that negatively affect people's well-being upon income arrival. These activities include amusement, gambling, shopping, and dining out. We also found that the type of health problems incurred differs by economic activity. Our data with detailed time stamps revealed that ambulance transport starts to increase during business hours and continues until midnight. All of these findings clearly demonstrate a connection between income, economic activity, and health deterioration.

### 5.1 Relation to the consumption literature

Our results indicate an increase in economic activities on payday. Rational consumers typically smooth their consumption over time, and we do not anticipate a sudden change in their behavior solely due to the arrival of expected income. However, considerable empirical research demonstrates that people increase consumption upon anticipated income arrival, often called excess sensitivity (Stephens, 2003; Gelman et al., 2014; Kueng, 2018). One major reason for excess sensitivity could be a relaxation of liquidity, as discussed in Section 4.6. However, excess sensitivity is reported not only among the economically disadvantaged but also in the more general population (Olafsson and Pagel, 2018). Our analysis using the survey reveals a result that is in line with this perspective. Possible explanations for excess sensitivity among people who are not liquidity constrained could include short-run impatience, mental accounting, and social interactions, as discussed in prior studies (Hastings and Washington, 2010; Kueng, 2018). Regarding short-run impatience, studies highlight the role of time and risk preferences to explain consumption changes associated with payment cycles. For example, the literature on within-month cycles in food consumption finds a decrease in calorie intake *before* payday (Shapiro, 2005) due to hyperbolic discounting (Mastrobuoni and Weinberg, 2009). In addition, a recent study shows that economically disadvantaged people tend to change their risk preferences around payday likely due to mental health and relative deprivation (Akesaka et al., 2023).

Mental accounting is the individual and household practice of recording, summarizing, analyzing, and reporting financial transactions and events, akin to organizational managerial accounting, aimed at tracking expenditures and maintaining fiscal discipline (Thaler, 1999). It is used to explain consumption reactions to an annual payment from the Alaska Permanent Fund, where people could regard unearned income as a windfall (Olafsson and Pagel, 2018). As pensions are the major source of income for the elderly population, this is less likely to be true in our case. By contrast, social interactions are likely to explain people's reaction in the context of pension payment. When the prominent and anticipated pension payment occurs simultaneously for everyone, individuals might perceive these moments as opportunities to engage in something noteworthy with other people such as dining together.

Our study setting provides a good environment to observe excess sensitivity in two ways. First, a previous study has shown that people tend to smooth consumption by delaying mortgage payments or shifting credit card payments if such a financial tool is available (Gelman et al., 2020). However, as discussed in Section 2, Japan is a cash-oriented country, and many individuals rely on cash for their economic activities. Notably, not having a credit card is common, particularly among older generations, signifying a lack of means for consumption smoothing. Second, expenditure and consumption are often recognized as distinct events because people do not necessarily consume goods when they purchase. Service utilization considered by our study such as dining out and playing in amusement arcades are considered typical examples of excess sensitivity because people utilize the service upon purchase.

## 5.2 Macro dynamics on health

The literature shows mortality decreases in economic downturns in the US, and the result is replicated with data from different countries (Ruhm, 2000; Gerdtham and Ruhm, 2006; Ariizumi and Schirle, 2012), although this tendency changed recently due to an increase in suicide and substance use (Ruhm, 2015). There are several channels to explain the procyclical nature of mortality. These include a decrease in labor time, a decrease in harmful consumption such as alcohol intake due to income decrease, fewer physical accidents from reduced economic activities, and reduced exposure to environmental toxicity during economic downturns. Among these channels, harmful consumption and reduced economic activities are related to our results. The consumption channel suggests that an increase in income leads to greater consumption of potentially harmful products, such as alcohol. The activity channel proposes that accidents decrease during economic downturns. In our study, we identify positive income shocks at the individual level that increase economic activities and subsequently negatively impact one's health. Our results also indicate that the health change is associated with alcohol consumption, as revealed in the analysis using diagnosis data, although the findings are not conclusive because the diagnosis category is broad and includes other types of health conditions.

## 5.3 Policy implications

Our findings suggest that the utilization of the healthcare system could be concentrated on a specific day, particularly on the day of pension payment. In many countries, including Japan, emergency medical services play a crucial role in the healthcare system by saving lives. Nevertheless, issues such as overcrowding in these services persist, highlighting the importance of efficiently allocating resources as a key concern in healthcare provision. With the payment cycles already determined, healthcare resources could be better prepared for these specific days. Detailed information, such as the timing of the increase within a day, would further enhance preparedness. Specifically, business hours on paydays in certain months experience a more pronounced increase and therefore require better preparation. Additionally, our results provide suggestive evidence that the surge in economic activity on paydays is triggered by the realization of liquidity, emphasizing the need for increased attention to economically disadvantaged areas.

While our primary focus is on the implications for the design of the healthcare system, our results are also relevant to the timing of public payments (LaPoint and Sakabe, 2022). The timing of payment for some public assistance programs in developed countries is arranged on an individual basis. For instance, economic stimulus packages were distributed based on the last digit of the social security number, and the payment timing for SNAP in the United States is based on the initial letter of the surname in certain places. As varying the timing of payment incurs some costs, decisions regarding differentiation in timing should carefully weigh the costs and benefits. Our results provide insight into one potential benefit—varying the timing of healthcare utilization—as a means of optimizing the allocation of limited resources in healthcare.

## 5.4 Conclusion

The literature has demonstrated the health response to income arrival. Our analysis, based on ambulance transport data, serves to bridge the gap between health changes and economic activity. We identify an increase in health changes following income receipt, which we attribute to specific economic activities, leveraging detailed data on the location and time of diseases or accidents.

# References


Akesaka, M., Eibich, P., Hanaoka, C. and Shigeoka, H. (2023). 'Temporal instability of risk preference among the poor: Evidence from payday cycles', American Economic Journal: Applied Economics, vol. 15(4), pp. 68–99.

Andersson, E., Lundborg, P. and Vikström, J. (2015). 'Income receipt and mortality — evidence from swedish public sector employees', Journal of Public Economics, vol. 131, pp. 21–32.

Ariizumi, H. and Schirle, T. (2012). 'Are recessions really good for your health? Evidence from canada', Social Science & Medicine, vol. 74(8), pp. 1224–1231.

Bond, T.N., Carr, J.B., Packham, A. and Smith, J. (2022). 'Hungry for success? SNAP timing, high-stakes exam performance, and college attendance', American Economic Journal: Economic Policy, vol. 14(4), pp. 51–79.

Carr, J.B. and Packham, A. (2019). 'SNAP benefits and crime: Evidence from changing disbursement schedules', The Review of Economics and Statistics, vol. 101(2), pp. 310–325.

Cesarini, D., Lindqvist, E., Östling, R. and Wallace, B. (2016). 'Wealth, health, and child development: Evidence from administrative data on swedish lottery players', The Quarterly Journal of Economics, vol. 131(2), pp. 687–738.

Dobkin, C. and Puller, S.L. (2007). 'The effects of government transfers on monthly cycles in drug abuse, hospitalization and mortality', Journal of Public Economics, vol. 91(11), pp. 2137–2157.

Erixson, O. (2017). 'Health responses to a wealth shock: Evidence from a swedish tax reform', Journal of Population Economics, vol. 30(4), pp. 1281–1336.

Evans, W.N. and Moore, T.J. (2011). 'The short-term mortality consequences of income receipt', Journal of Public Economics, vol. 95(11), pp. 1410–1424.

Evans, W.N. and Moore, T.J. (2012). 'Liquidity, economic activity, and mortality', The Review of Economics and Statistics, vol. 94(2), pp. 400–418.

Fire and Disaster Management Agency (2020). The 2020 White Paper on Fire Service.

Gelman, M., Kariv, S., Shapiro, M.D., Silverman, D. and Tadelis, S. (2014). 'Harnessing naturally occurring data to measure the response of spending to income', Science, vol. 345(6193), pp. 207–212.

Gelman, M., Kariv, S., Shapiro, M.D., Silverman, D. and Tadelis, S. (2020). 'How individuals respond to a liquidity shock: Evidence from the 2013 government shutdown', Journal of Public Economics, vol. 189, p. 103917.

Gerdtham, U.G. and Ruhm, C.J. (2006). 'Deaths rise in good economic times: Evidence from the OECD', Economics and Human Biology, vol. 4(3), pp. 298–316.

Goldin, J., Homonoff, T. and Meckel, K. (2022). 'Issuance and incidence: SNAP benefit cycles and grocery prices', American Economic Journal: Economic Policy, vol. 14(1), pp. 152–178.

Gross, T., Layton, T. and Prinz, D. (2022). 'The liquidity sensitivity of healthcare consumption: Evidence from social security payments', American Economics Review: Insights, vol. 4(2), pp. 175–190.

Gross, T., Notowidigdo, M.J. and Wang, J. (2014). 'Liquidity constraints and consumer bankruptcy: Evidence from tax rebates', The Review of Economics and Statistics, vol. 96(3), pp. 431–443.

Hastings, J. and Washington, E. (2010). 'The first of the month effect: Consumer behavior and store responses', American Economic Journal: Economic Policy, vol. 2(2), pp. 142–162.

Kueng, L. (2018). 'Excess sensitivity of High-Income consumers*', The Quarterly Journal of Economics, vol. 133(4), pp. 1693–1751.

LaPoint, C. and Sakabe, S. (2022). 'Coming in at a trickle: The optimal frequency of public benefit payments', Mimeo.

Mastrobuoni, G. and Weinberg, M. (2009). 'Heterogeneity in intra-monthly consumption patterns, Self-Control, and savings at retirement', American Economic Journal: Economic Policy, vol. 1(2), pp. 163–189.

Olafsson, A. and Pagel, M. (2018). 'The liquid Hand-to-Mouth: Evidence from personal finance management software', The Review of Financial Studies, vol. 31(11), pp. 4398–4446.

Östling, R., Cesarini, D. and Lindqvist, E. (2020). ‘Association between lottery prize size and self-reported health habits in swedish lottery players’, JAMA Netw Open, vol. 3(3), pp. e1919713–e1919713.

Ruhm, C.J. (2000). ‘Are recessions good for your health?*’, The Quarterly Journal of Economics, vol. 115(2), pp. 617–650.

Ruhm, C.J. (2015). ‘Recessions, healthy no more?’, Journal of Health Economics, vol. 42, pp. 17–28.

Sakamaki, T. (2019). ‘The advancement of the digital economy and diversification of payment methods [Dezitaru keizai no shinten to shiharai syudan no tayoka]’, Report on the Study Group on Innovation in the Digital Age, Chapter 1, available at: https://www.mof.go.jp/pri/research/conference/fy2018/digital2018$_{r}eport01.pdf$.

Schwartz, B.G., Kloner, R.A. and Naghavi, M. (2018). ‘Acute and subacute triggers of cardiovascular events’, The American Journal of Cardiology, vol. 122(12), pp. 2157–2165.

Shapiro, J.M. (2005). ‘Is there a daily discount rate? evidence from the food stamp nutrition cycle’, Journal of Public Economics, vol. 89(2), pp. 303–325.

Stephens, M. (2003). ‘“3rd of the month”: Do social security recipients smooth consumption between checks?’, The American Economic Review, vol. 93(1), pp. 406–422.

Stephens, M. and Unayama, T. (2011). ‘The consumption response to seasonal income: Evidence from Japanese public pension benefits’, The American Economic Review, vol. 3(4), pp. 86–118.

Thaler, R.H. (1999). ‘Mental accounting matters’, Journal of Behavioral Decision Making, vol. 12(3), pp. 183–206.

Yoshizawa, K., Maebashi, K., Yanagihara, H., and Kadokawa, Y.(2021). ‘Trends in banknotes during the COVID-19 pandemic [Koronaka niokeru ginkouken no doukou]’, Bank of Japan Review, 2021-J-15, available at: https://www.boj.or.jp/research/wps$_{r}ev/rev_{2}021/data/rev21j15.pdf$.

# Appendix

# A Data

Table A1: Data availability

| | Data availability | | Availability of detailed categories | | | |
|---|---|---|---|---|---|---|
| | | | Public space | | Disease code | |
| | All others | Tokyo | All others | Tokyo | All others | Tokyo |
| 2007 | ✓ | n.a. | n.a. | n.a. | n.a. | n.a. |
| 2008 | ✓ | n.a. | n.a. | n.a. | n.a. | n.a. |
| 2009 | ✓ | n.a. | n.a. | n.a. | n.a. | n.a. |
| 2010 | ✓ | n.a. | n.a. | n.a. | n.a. | n.a. |
| 2011 | ✓ | n.a. | n.a. | n.a. | n.a. | n.a. |
| 2012 | ✓ | n.a. | n.a. | n.a. | n.a. | n.a. |
| 2013 | ✓ | n.a. | n.a. | n.a. | n.a. | n.a. |
| 2014 | ✓ | n.a. | n.a. | n.a. | n.a. | n.a. |
| 2015 | ✓ | n.a. | ✓ | n.a. | ✓ | n.a. |
| 2016 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2017 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2018 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2019 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

*Notes*: Ambulance transport data are obtained from the Fire and Disaster Management Agency. The data are provided separately by the Tokyo Fire Department and by all other fire departments. A ✓indicates that the data are available, while n.a. indicates that the data are not available.

## Table A2: Definition of categories

| | Main category | | Subcategory | |
|---|---|---|---|---|
| | Category | Definition | Category | Example/Definition |
| Location | Residence | | | |
| | Public space | | Theater/Museum | Theaters, movie theaters, halls, libraries, museums, galleries |
| | | | Restaurant/Bar | restaurants, bars, night clubs |
| | | | Amusement arcade | Amusement place, *pachinko* parlor, bowling center, public bath |
| | | | Shopping center | Department store, supermarket, small shops, shopping malls |
| | | | Hospital/Nursing home | Hospitals, clinics, nursing homes |
| | | | School | Preschool, K12, universities, vocational colleges, special needs schools |
| | | | Station/Airport | Stations, trains, airports |
| | | | Hotel | Hotels, accommodations |
| | | | Other | Temples, churches, parks, city halls, pools |
| | Workplace | | | |
| | Road | | | |
| Incidence type | Traffic accident | Traffic-involved accidents | | |
| | Injury | Injuries caused by events other than traffic accidents, criminal incidences, self-harms, work-related accidents, sports competition, swimming, or natural disasters | | |
| | Illness | | Cerebrovascular diseases | IX Diseases of the circulatory system, Stroke(a-0904) and Other cerebrovascular diseases(a-0905) |
| | | | Heart diseases | IX Diseases of the circulatory system, Hypertension(a-0901) to other heart diseases(a-0903), and other cardiovascular diseases(a-0906) |
| | | | Digestive diseases | XI Diseases of the digestive system |
| | | | Respiratory diseases | X Diseases of the respiratory system |
| | | | Mental and behavioral disorders | V Mental and behavioral disorders |
| | | | Diseases of nervous system | VI Disease of the nervous system, VII Diseases of the eye and adnexa, VIII Diseases of the ear and mastoid process |
| | | | Diseases of genitourinary system | XIV Diseases of the genitourinary system |
| | | | Cancer | II Neoplasms |
| | | | Other | I, III, IV, XII, XIII, XV, XVI, XVII, XIX, XX, and XXI |
| | | | Undiagnosed or not classified | IVIII Symptoms, signs and abnormal clinical and laboratory findings, not elsewhere classified |
| | Other | Criminal incidences, self-harms, work-related accidents, sports competition, swimming, or natural disasters, not elsewhere classified | | |
| Severity | Death | | | |
| | Fatal | Fatal is a life-threatening conditions | | |
| | Severe | Requires hospitalization for 3 or more weeks | | |
| | Serious | Does not fall in other categories | | |
| | Mild | Does not require hospitalization | | |

*Notes*: The main categories and subcategories of illness are defined in the dataset. We further specify subcategories for public spaces by consolidating the 27 categories provided in the dataset into nine overarching categories. The definition of diagnosis categories is based on the Overview of Emergency Aid available at https://www.fdma.go.jp/publication/rescue/items/kkkg$_r$02$_0$1$_k$*yukyu.pdf*.

Table A3: Summary statistics of the original data, all

| | N | % Female | Age | | Location (%) | | | | Type (%) | | | | Severity (%) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Percent | Mean | SD | Home | Public Space | Workplace | Road | Accident | Injury | Illness | Other | Death/Fatal | Serious | Severe | Mild |
| 2007 | 3555127 | 47.62 | 56.345 | 26.184 | 55.52 | 24.54 | 2.75 | 17.18 | 13.24 | 13.03 | 59.90 | 13.83 | 2.35 | 10.17 | 37.09 | 50.39 |
| 2008 | 3931716 | 47.48 | 57.469 | 26.036 | 55.81 | 24.86 | 2.68 | 16.65 | 12.39 | 13.42 | 60.35 | 13.83 | 2.11 | 9.87 | 37.86 | 50.16 |
| 2009 | 4053987 | 47.54 | 57.800 | 26.189 | 56.62 | 24.74 | 2.39 | 16.24 | 12.01 | 13.51 | 60.91 | 13.56 | 2.01 | 9.67 | 38.35 | 49.97 |
| 2010 | 4327256 | 47.84 | 58.956 | 25.964 | 57.03 | 24.93 | 2.51 | 15.53 | 11.44 | 13.57 | 61.68 | 13.30 | 2.04 | 9.41 | 38.78 | 49.77 |
| 2011 | 4543799 | 47.95 | 59.650 | 25.900 | 57.76 | 24.92 | 2.49 | 14.83 | 10.83 | 13.97 | 62.19 | 13.02 | 2.01 | 9.19 | 38.85 | 49.95 |
| 2012 | 4603173 | 48.17 | 60.160 | 25.914 | 55.96 | 28.18 | 2.30 | 13.56 | 10.48 | 14.09 | 62.64 | 12.79 | 2.06 | 8.30 | 38.74 | 50.91 |
| 2013 | 5224172 | 48.08 | 60.287 | 25.768 | 57.21 | 25.67 | 2.48 | 14.64 | 10.15 | 14.12 | 63.09 | 12.65 | 1.94 | 8.73 | 39.49 | 49.84 |
| 2014 | 5279417 | 48.08 | 60.759 | 25.769 | 57.26 | 26.10 | 2.48 | 14.16 | 9.70 | 14.52 | 63.21 | 12.57 | 1.91 | 8.60 | 40.34 | 49.15 |
| 2015 | 4805224 | 48.51 | 61.456 | 25.742 | 57.28 | 26.81 | 2.47 | 13.44 | 9.18 | 14.58 | 63.56 | 12.68 | 1.84 | 8.44 | 40.88 | 48.85 |
| 2016 | 5594941 | 48.56 | 61.310 | 25.959 | 57.59 | 26.72 | 2.51 | 13.18 | 8.35 | 15.25 | 65.00 | 11.41 | 2.30 | 11.56 | 42.90 | 43.24 |
| 2017 | 5826673 | 48.68 | 61.963 | 25.954 | 57.36 | 27.22 | 2.50 | 12.92 | 8.17 | 15.52 | 64.78 | 11.53 | 1.85 | 7.93 | 41.64 | 48.58 |
| 2018 | 5867716 | 48.97 | 62.485 | 25.816 | 57.87 | 27.23 | 2.67 | 12.23 | 7.34 | 15.43 | 65.87 | 11.36 | 1.72 | 7.76 | 41.67 | 48.85 |
| 2019 | 5978155 | 49.03 | 62.668 | 26.064 | 58.10 | 27.54 | 2.49 | 11.87 | 6.94 | 15.62 | 66.17 | 11.27 | 1.70 | 7.72 | 42.57 | 48.01 |
| Total | 6.36e+07 | 48.30 | 60.541 | 25.988 | 57.20 | 26.14 | 2.53 | 14.13 | 9.73 | 14.48 | 63.32 | 12.47 | 1.97 | 8.96 | 40.22 | 48.86 |

*Notes*: Ambulance transport data are obtained from the Fire and Disaster Management Agency. The table describes the original case-level data using all the available data in Appendix Table A1 before aggregating at the daily level data that we use for our analysis.

Table A4: Summary statistics of the original data, 65-79 years old

| | N | % Female | Age | | Location (%) | | | | Type (%) | | | | Severity (%) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Percent | Mean | SD | Home | Public Space | Workplace | Road | Accident | Injury | Illness | Other | Death/Fatal | Serious | Severe | Mild |
| 2007 | 718304 | 44.61 | 72.629 | 4.281 | 64.11 | 23.37 | 1.06 | 11.47 | 7.25 | 13.31 | 66.09 | 13.35 | 2.96 | 13.29 | 43.36 | 40.39 |
| 2008 | 802307 | 44.31 | 72.677 | 4.292 | 63.97 | 23.61 | 1.09 | 11.33 | 7.06 | 13.76 | 65.80 | 13.37 | 2.75 | 13.23 | 43.81 | 40.21 |
| 2009 | 869274 | 44.43 | 72.679 | 4.306 | 64.16 | 23.40 | 1.00 | 11.44 | 7.10 | 14.00 | 65.88 | 13.02 | 2.58 | 12.70 | 43.79 | 40.92 |
| 2010 | 959793 | 44.72 | 72.778 | 4.277 | 64.68 | 23.21 | 1.03 | 11.08 | 6.81 | 14.05 | 66.53 | 12.61 | 2.52 | 12.01 | 43.73 | 41.73 |
| 2011 | 1013810 | 44.76 | 72.872 | 4.227 | 65.18 | 22.93 | 1.07 | 10.83 | 6.50 | 14.48 | 66.81 | 12.21 | 2.39 | 11.51 | 43.50 | 42.60 |
| 2012 | 1053411 | 44.77 | 72.838 | 4.273 | 62.65 | 25.83 | 0.98 | 10.54 | 6.42 | 14.57 | 66.98 | 12.04 | 2.46 | 10.51 | 43.28 | 43.75 |
| 2013 | 1282242 | 44.51 | 72.683 | 4.341 | 64.33 | 23.02 | 1.18 | 11.48 | 6.32 | 14.68 | 67.42 | 11.57 | 2.14 | 10.24 | 43.34 | 44.28 |
| 2014 | 1315231 | 44.31 | 72.604 | 4.394 | 64.08 | 23.25 | 1.25 | 11.41 | 6.23 | 14.99 | 67.27 | 11.51 | 2.12 | 10.00 | 43.96 | 43.92 |
| 2015 | 1307446 | 44.53 | 72.587 | 4.397 | 64.21 | 23.47 | 1.31 | 11.01 | 6.15 | 14.73 | 67.41 | 11.70 | 2.03 | 9.77 | 44.07 | 44.14 |
| 2016 | 1477851 | 44.22 | 72.565 | 4.361 | 64.00 | 23.28 | 1.39 | 11.33 | 5.85 | 15.37 | 68.05 | 10.74 | 2.60 | 12.94 | 45.03 | 39.44 |
| 2017 | 1526934 | 43.91 | 72.623 | 4.297 | 63.82 | 23.54 | 1.45 | 11.18 | 5.75 | 15.54 | 68.00 | 10.71 | 2.08 | 9.24 | 44.83 | 43.85 |
| 2018 | 1566268 | 44.00 | 72.688 | 4.236 | 64.48 | 23.02 | 1.56 | 10.94 | 5.34 | 15.43 | 68.62 | 10.61 | 1.91 | 9.09 | 44.66 | 44.33 |
| 2019 | 1588206 | 43.84 | 72.851 | 4.208 | 64.17 | 23.47 | 1.53 | 10.83 | 5.18 | 15.68 | 68.41 | 10.73 | 1.91 | 9.08 | 45.57 | 43.44 |
| Total | 1.55e+07 | 44.32 | 72.694 | 4.302 | 64.22 | 23.34 | 1.28 | 11.16 | 6.16 | 14.83 | 67.39 | 11.63 | 2.27 | 10.75 | 44.22 | 42.75 |

*Notes*: The data show ambulance transports for people aged between 65 and 79 years. Ambulance transport data are obtained from the Fire and Disaster Management Agency. The table describes the original case-level data for patients aged 65 to 79 using all the available data in Appendix Table A1 before aggregating at the daily level data that we use for our analysis.

Table A5: Summary statistics

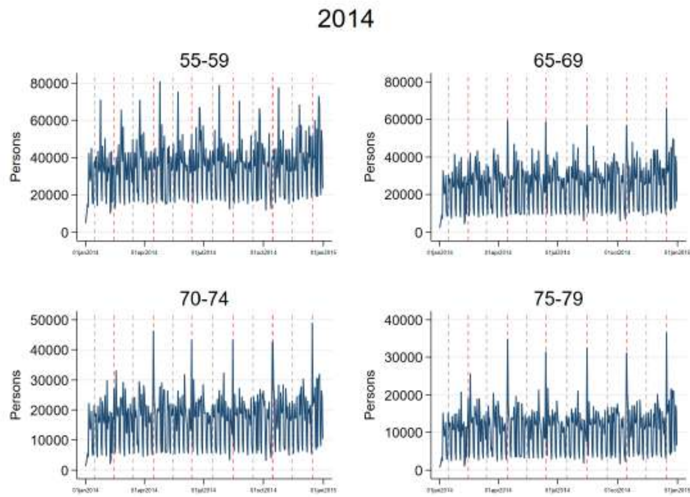
| | | N | Mean | S.D. | Min | Max |
|---|---|---|---|---|---|---|
| Total | | 3900 | 3259.63 | 852.62 | 1569 | 5849 |
| Location | Residence | 3900 | 1943.02 | 696.45 | 313 | 3844 |
| | Public space | 3900 | 707.18 | 263.25 | 100 | 1413 |
| | Work place | 3900 | 38.72 | 23.02 | 0 | 173 |
| Type | Road | 3900 | 337.55 | 124.88 | 37 | 723 |
| | Accident | 3900 | 199.74 | 45.23 | 72 | 353 |
| | Injury | 3900 | 481.53 | 151.75 | 179 | 1086 |
| | Illness | 3900 | 2191.25 | 602.05 | 1030 | 4250 |
| | Other | 3900 | 376.51 | 125.85 | 113 | 726 |
| Severity | Death/Fatal | 3900 | 72.87 | 22.80 | 24 | 167 |
| | Serious | 3900 | 344.34 | 85.71 | 161 | 759 |
| | Severe | 3900 | 1414.29 | 413.08 | 674 | 2787 |
| | Mild | 3900 | 1369.14 | 409.89 | 589 | 2814 |
| Public space | Theater/Museum | 1500 | 24.40 | 10.48 | 4 | 73 |
| | Restaurant/Bar | 1500 | 57.77 | 23.36 | 14 | 194 |
| | Amusement arcade | 1500 | 34.66 | 14.07 | 7 | 89 |
| | Shopping center | 1500 | 75.42 | 17.13 | 30 | 148 |
| | Hospital/Nursing home | 1500 | 571.63 | 144.12 | 246 | 943 |
| | School | 1500 | 6.55 | 5.74 | 0 | 69 |
| | Station/Airport | 1500 | 32.91 | 9.22 | 2 | 75 |
| | Hotel | 1500 | 29.76 | 8.97 | 10 | 68 |
| | Other | 1500 | 73.09 | 17.18 | 35 | 161 |
| Diagnosis | Cerebrovascular diseases | 1500 | 280.28 | 32.96 | 194 | 404 |
| | Heart diseases | 1500 | 294.25 | 40.79 | 198 | 441 |
| | Digestive diseases | 1500 | 259.27 | 25.78 | 179 | 388 |
| | Respiratory diseases | 1500 | 238.72 | 64.48 | 147 | 623 |
| | Mental and behavioral disorders | 1500 | 43.67 | 7.90 | 19 | 79 |
| | Neurological diseases | 1500 | 121.97 | 15.33 | 78 | 189 |
| | Kidney diseases | 1500 | 83.69 | 15.84 | 47 | 150 |
| | Cancer | 1500 | 72.01 | 12.41 | 40 | 132 |
| | Other | 1500 | 509.98 | 112.32 | 340 | 1304 |
| | Undiagnosed or not classified | 1500 | 954.37 | 150.96 | 600 | 1555 |

*Notes*: The table describes the summary statistics of daily data of ambulance transport cases for the entire sample as well as by incidence location, type, severity, subcategories of public space, and diagnosis for illness. Ambulance transport data are obtained from the Fire and Disaster Management Agency. The definition or examples of each category is shown in Appendix Table A2.

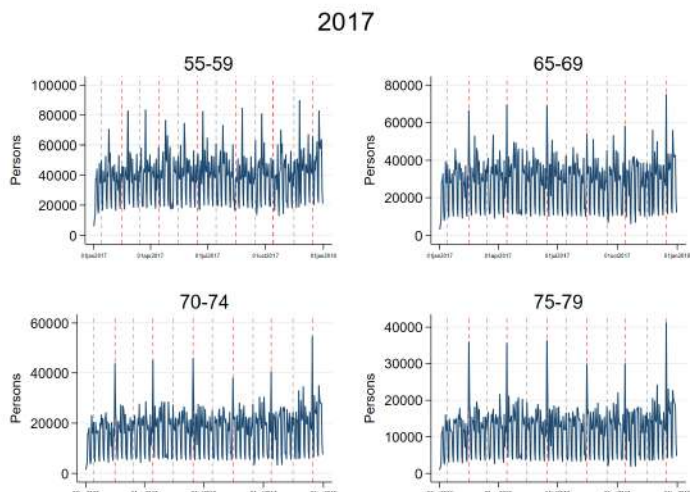
# B Additional figures and tables

Figure B1: Daily number of individuals who withdraw cash by age group, 2014 and 2017

(a)



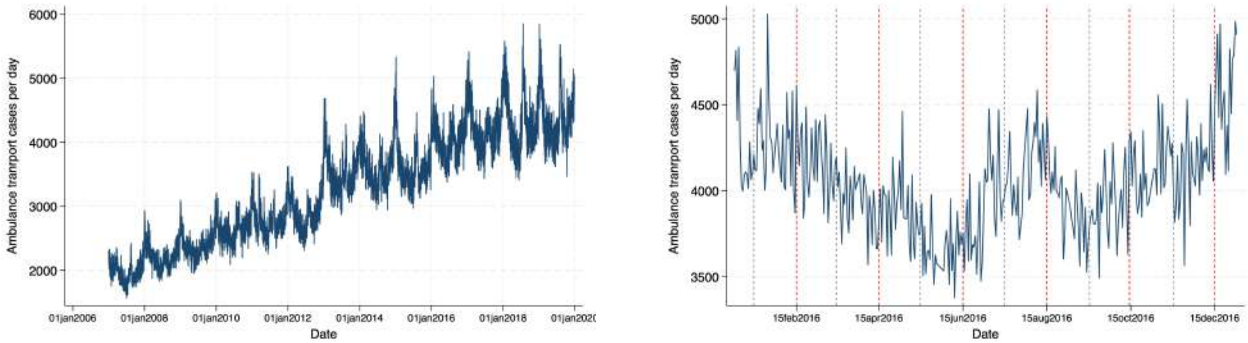

(b)




*Notes*: This figure shows the daily number of individuals who withdrew cash in each age category in 2014 (Panel (a)) and in 2017 (Panel (b)). The red dashed lines show the pension payday, typically on the 15th of even-numbered months, and the gray dashed line shows the corresponding day in odd-numbered months.

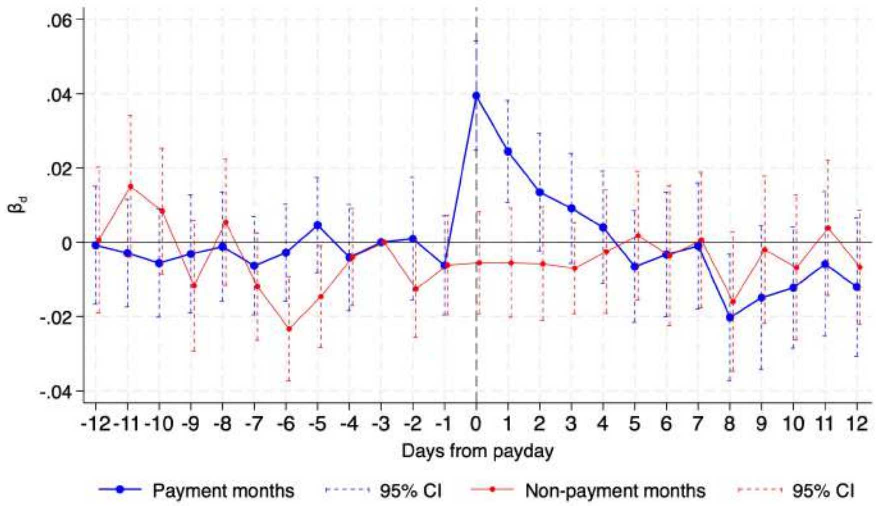
Figure B2: Daily number of ambulance transports

(a) 2007-2019 (b) 2016




*Notes*: This figure shows the daily number of ambulance transport cases in our study sample. Panels (a) and (b) show the plot for the entire study period (2007-2019) and 2016, respectively. In Panel (b), the red dashed line shows the pension payday, and the gray dashed line shows the corresponding day in nonpayment months.

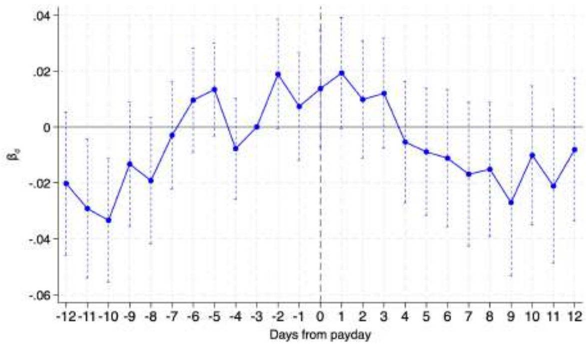
Figure B3: Relative number of ambulance transports for pension payment months and nonpayment months



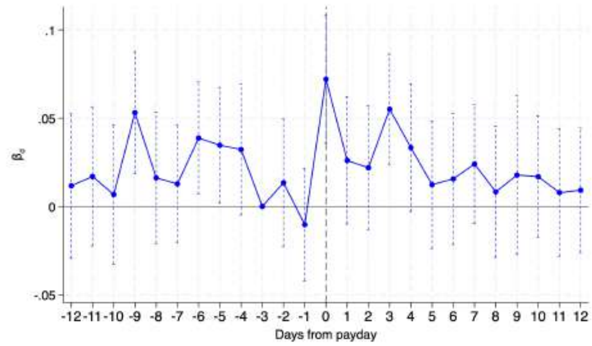

*Notes*: This figure shows the change in ambulance transport cases on each day of the synthetic month from the three days before the payday in payment and nonpayment months, using all the ambulance transport data between 2007 and 2019. The number of observations is 1,950. The dotted bar shows the 95 confidence interval. $d = 0$ shows the payday for payment months and the corresponding day for nonpayment months. The blue line shows payment months, and the red line shows nonpayment months. The numbers show an increase in ambulance transport cases compared to three days before the payday.

Figure B4: Impact of pension payday on ambulance transport by incidence location

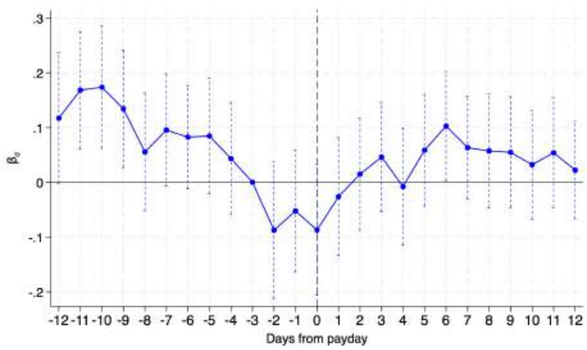
(a) Residence



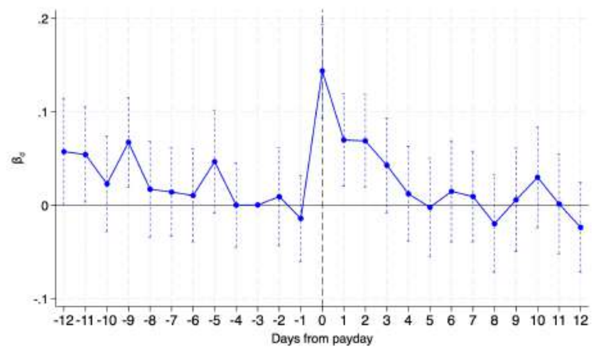

(b) Public space




(c) Workplace

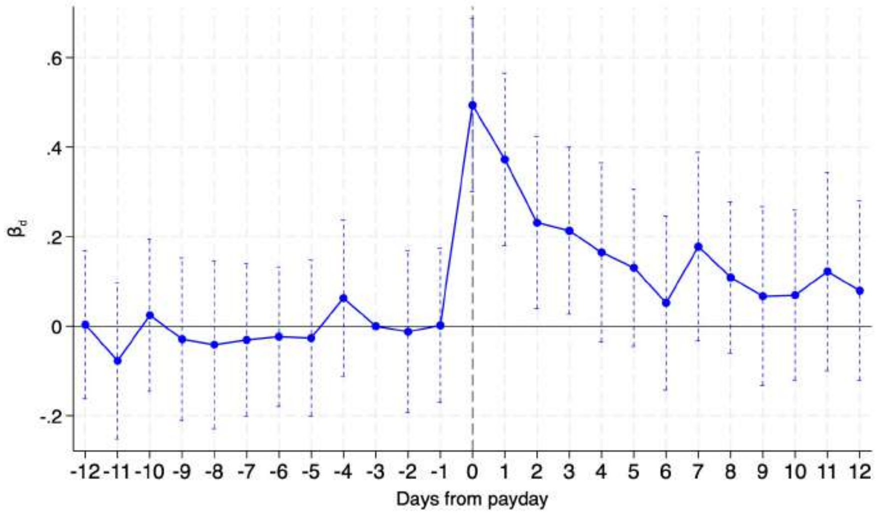



(d) Road



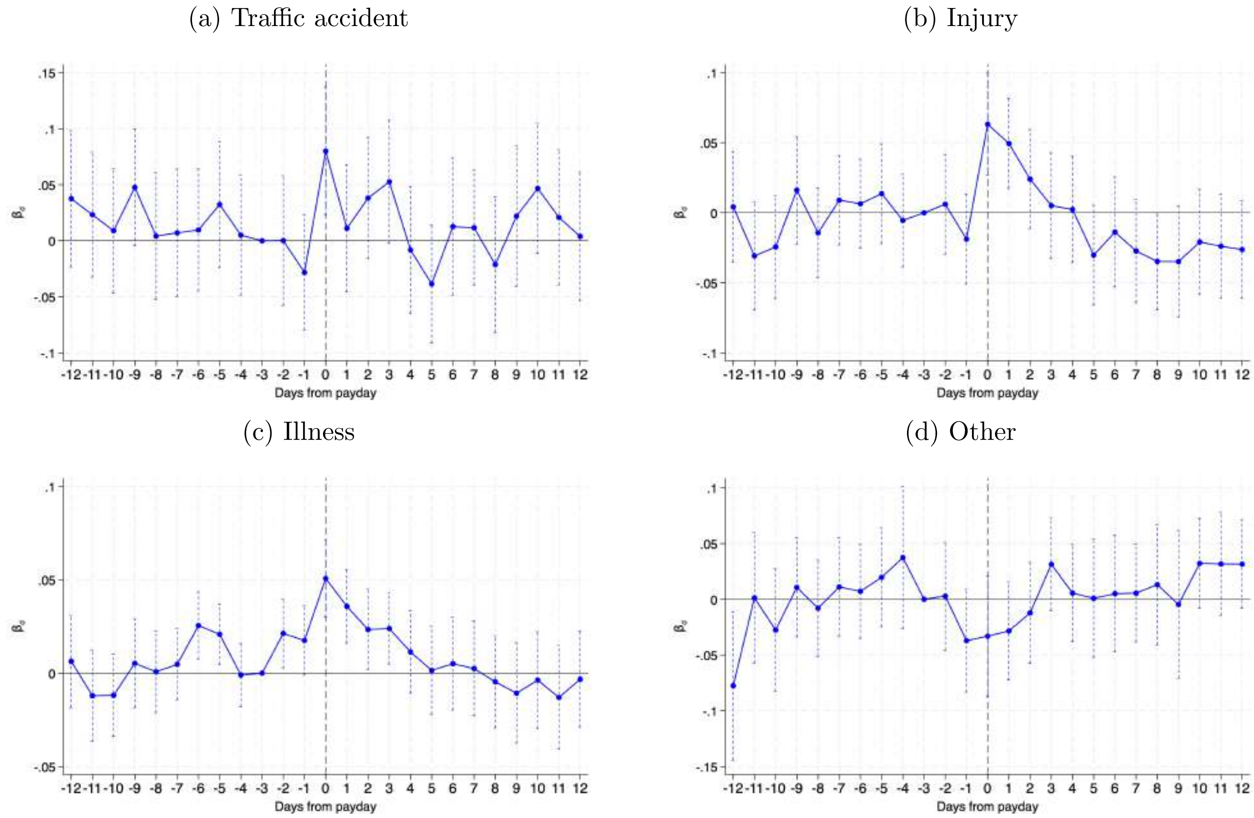

*Notes*: This figure shows the coefficient estimates of $\beta_d$, where $d = \{-12, -11, ..., -1, 0, 1, .., 11, 12\}$ from Equation (1), using all ambulance transport data between 2007 and 2019. The number of observations is 3,900. The dotted bar shows the 95 percent confidence interval. $d = 0$ shows the payday. The coefficient estimates show the difference in the relative increase in ambulance transport cases compared to the reference day, three days before the payday, between payment and nonpayment months.

Figure B5: Impact of pension payment on ambulance transport from amusement arcades



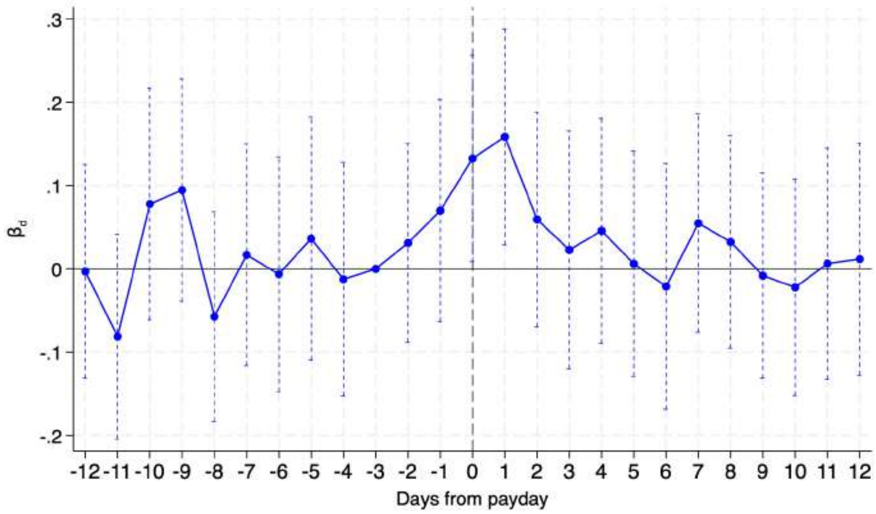

*Notes*: This figure shows the coefficient plot of $\beta_d$, where $d = \{-12, -11, ..., -1, 0, 1, .., 11, 12\}$ from Equation (1), using all the ambulance transport data between 2007 and 2019. The number of observations is 1,500. The dotted bar shows the 95 confidence interval. $d = 0$ shows the payday. The numbers show the difference in the relative increase in ambulance transport cases compared to the reference day, three days before the payday, between payment and nonpayment months. The examples of amusement arcades is presented in Appendix A2.

Figure B6: Impact of pension payday on ambulance transport by incidence type




*Notes*:This figure shows the coefficient estimates of $\beta_d$, where $d = \{-12, -11, ..., -1, 0, 1, .., 11, 12\}$ from Equation (1), using all ambulance transport data between 2007 and 2019. The number of observations is 3,900. The dotted bar shows the 95 percent confidence interval. $d = 0$ shows the payday. The coefficient estimates show the difference in the relative increase in ambulance transport cases compared to the reference day, three days before the payday, between payment and nonpayment months. The definition of incidence type is presented in Appendix Table A2.

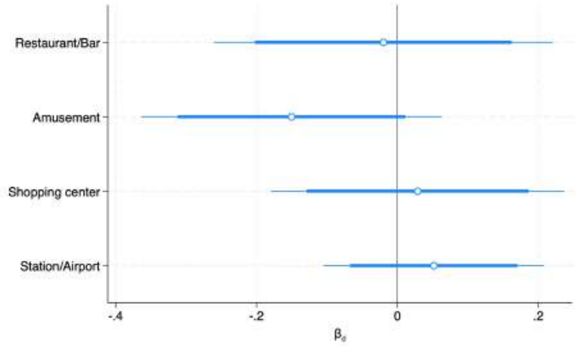
Figure B7: Impact of pension payday on ambulance transport due to mental and behavioral disorder



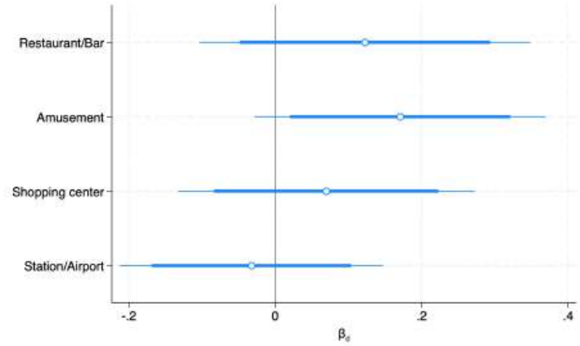

*Notes*: This figure shows the coefficient estimates of $\beta_d$, where $d = \{-12, -11, ..., -1, 0, 1, .., 11, 12\}$ from Equation (1), using all ambulance transport data between 2015 and 2019. The number of observations is 1,500. The dotted bar shows the 95 percent confidence interval. $d = 0$ shows the payday. The coefficient estimates show the difference in the relative increase in ambulance transport cases compared to the reference day, three days before the payday, between payment and nonpayment months. The definition of mental and behavioral disorder is presented in Appendix Table A2.

Figure B8: Payday impact by location of incidence and diagnosis

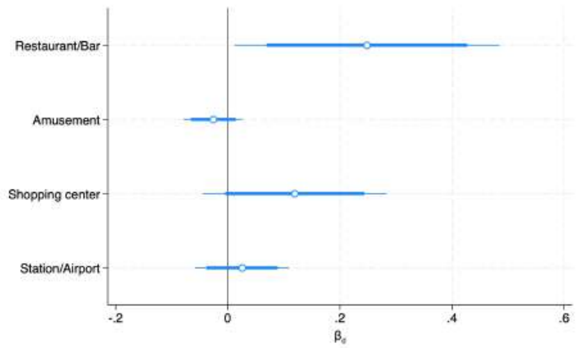
(a) Cerebrovascular diseases



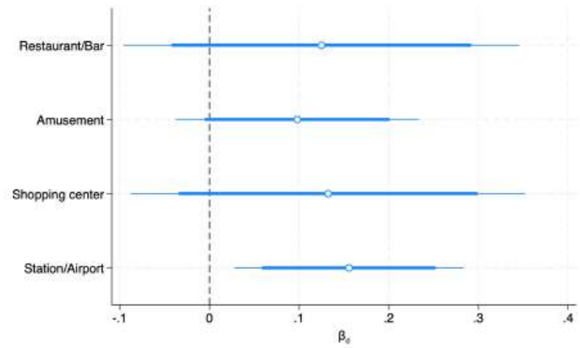

(b) Heart diseases




(c) Mental and behavioral disorders



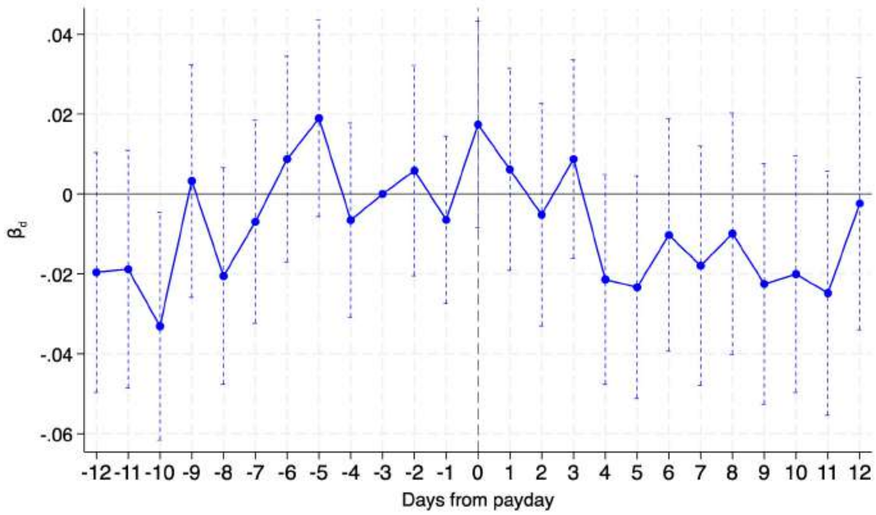

(d) Injury



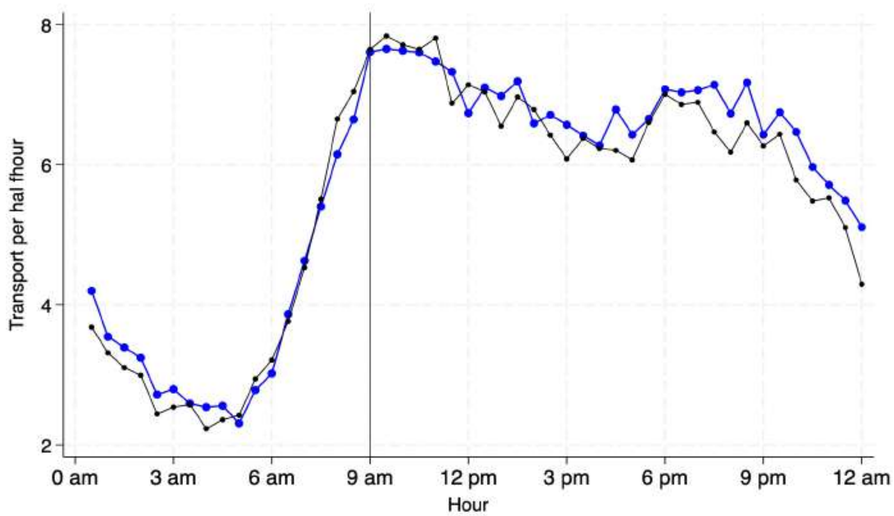

*Notes*: This figure shows the coefficient plot of $\beta_0$ of Equation (1), using the ambulance transport data between 2015 and 2019. The number of observations is 1,500. The thin bar shows the 99% confidence interval, and the thick bar shows the 95% confidence interval. The numbers show the difference in the relative increase from the reference day in ambulance transport cases between payment and nonpayment months. The reference day is three days before the payday. The definition of disease category and examples of each location category are presented in Appendix Table A2.

Figure B9: Falsification test: Analysis for those 55 to 59 years old

(a) Main results

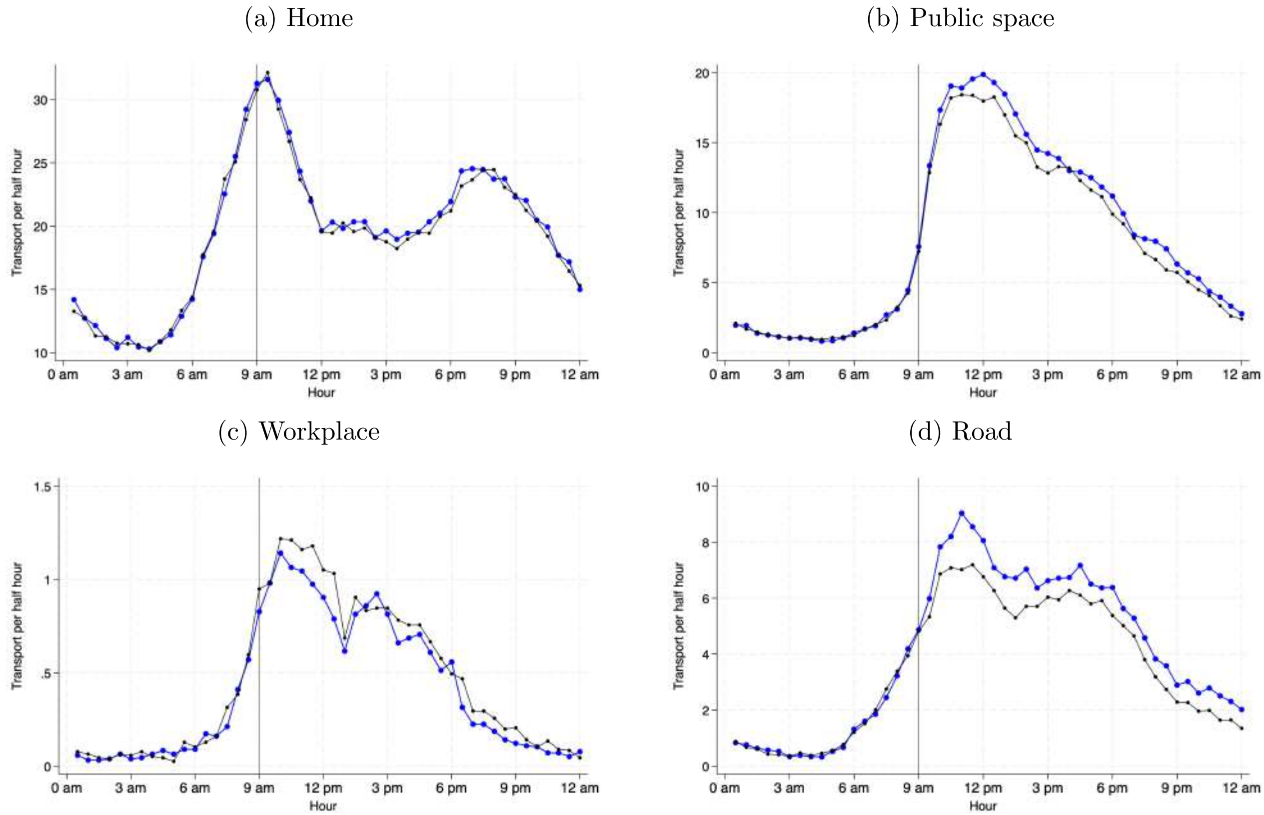



(b) By hour



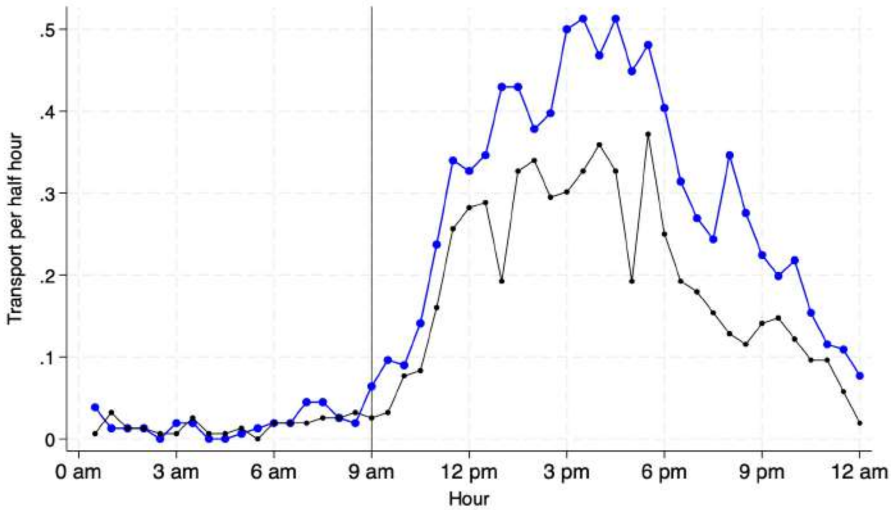

*Notes*: Panel (a) shows the coefficient estimates of $\beta_d$, where $d = \{-12, -11, ..., -1, 0, 1, .., 11, 12\}$ from Equation (1), using all the ambulance transport data between 2007 and 2019. The number of observations is 3,900. The dotted bar shows the 95 percent confidence interval. $d = 0$ shows the payday. The coefficient estimates show the difference in the relative increase in ambulance transport cases compared to the reference day, three days before the payday, between payment and nonpayment months. Panel (b) shows the plot of the average number of ambulance transport cases in each 30 minute bin over the sample period, 2007 to 2019, for those aged 55 to 59 years. The blue line shows payment months, and the black line shows nonpayment months.

Figure B10: Ambulance transport by half-hour on the payday by incidence location



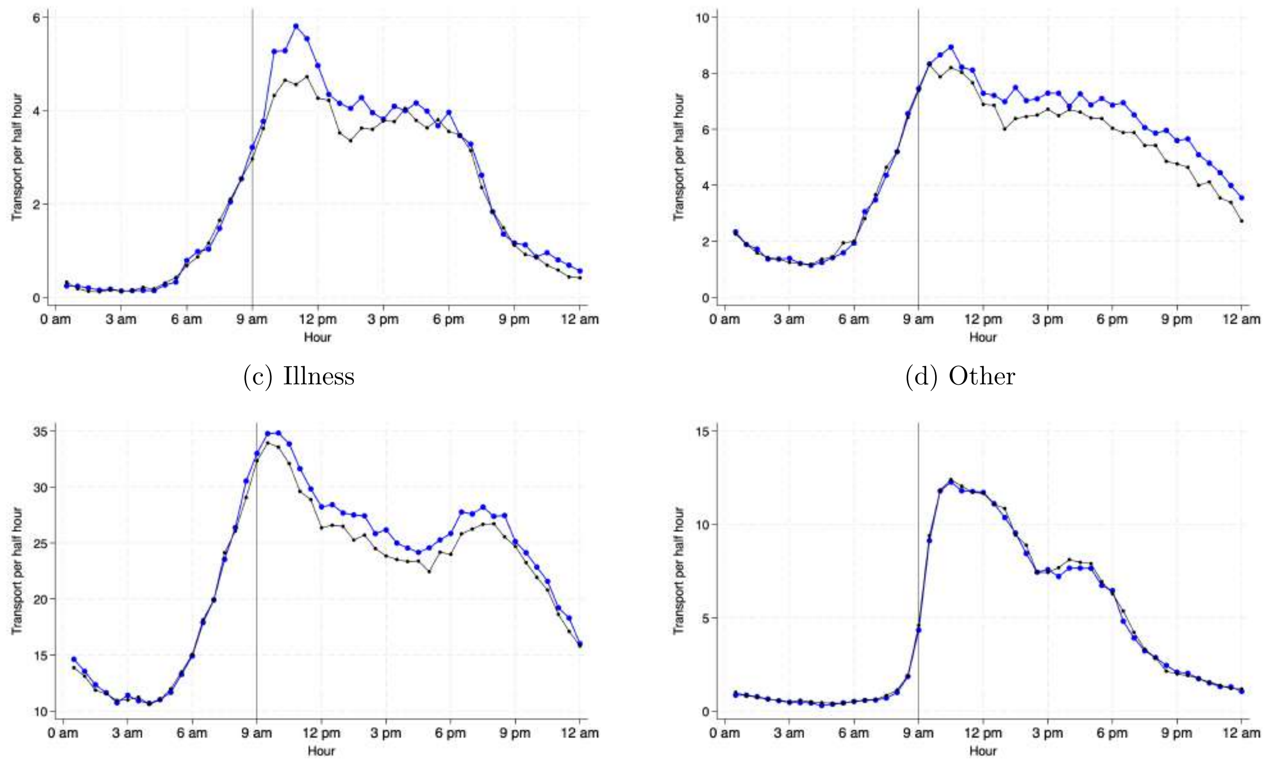

*Notes*: This figure shows the plot of the average number of ambulance transport cases in each 30 minute bin over the sample period, 2007 to 2019, for each incidence location. In each panel there are two lines. The blue line shows payment months, and the black line shows nonpayment months. The vertical line represents 9:00 am.

Figure B11: Ambulance transport from amusement arcades by half-hour on the payday




*Notes*: This figure shows the plot of the average number of ambulance transport cases in each 30 minute bin over the sample period, 2015 to 2019, for each incidence location. The blue line shows payment months, and the black line shows nonpayment months. The vertical line represents 9:00 am. The examples of amusement arcades are presented in Appendix Table A2.

Figure B12: Ambulance transport by half-hour on the payday by incidence type




(a) Traffic accident

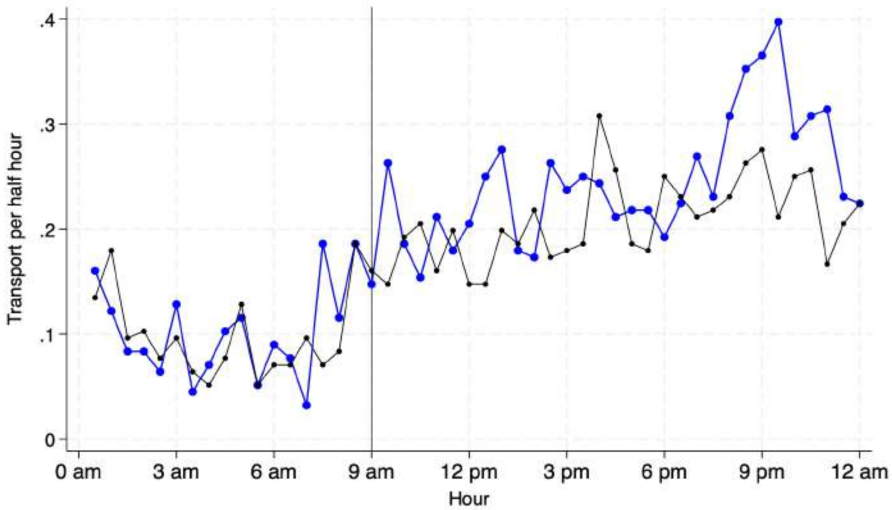
(b) Injury

(c) Illness

(d) Other

*Notes*: This figure shows the plot of the average number of ambulance transport cases in each 30 minute bin over the sample period, 2007 to 2019, for each incidence location. In each panel, there are two lines. The blue line shows payment months, and the black line shows nonpayment months. The vertical line represents 9:00 am. The definition of each incidence type is presented in Appendix Table A2.

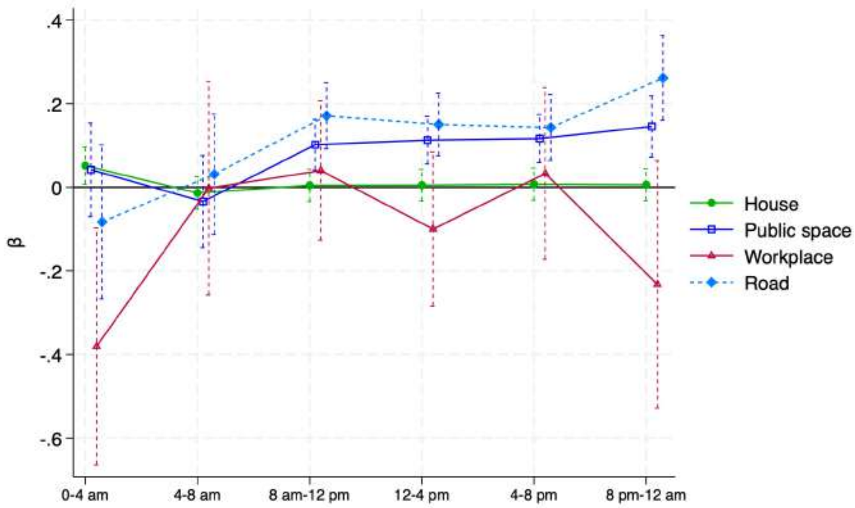
Figure B13: Ambulance transport due to mental and behavioral disorder by half-hour on the payday



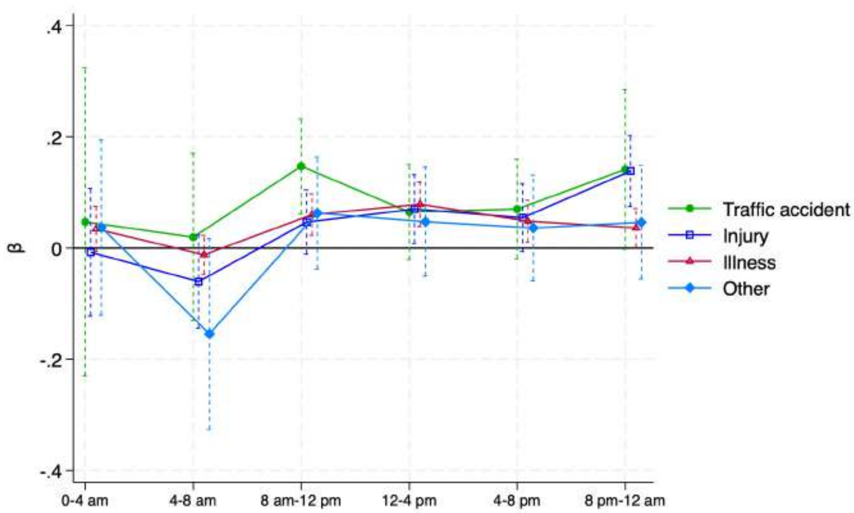

*Notes*: This figure shows the plot of the average number of ambulance transport cases in each 30 minute bin over the sample period, 2015 to 2019, for each incidence location. The blue line shows payment months, and the black line shows nonpayment months. The vertical line represents 9:00 am. The definition of mental and behavioral disorder is presented in Appendix Table A2.

Figure B14: Increase in ambulance transport on the payday by incidence location and incidence type, regression analysis

(a) Incidence location



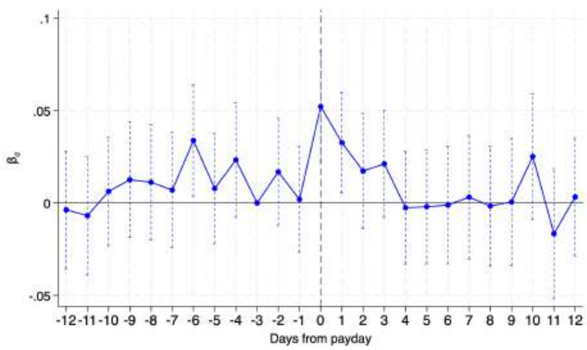

(b) Incidence type



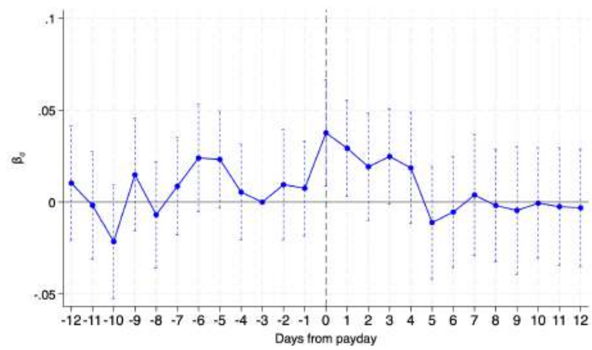

*Notes*: This figure shows the coefficient plot of $\beta$ from Equation (2) for each four-hour interval. The dotted bar shows the 95 percent confidence interval. The regressions were performed separately for each six intervals. For each analysis, the number of observations is 312. The results are presented for all individuals between 65 and 79 by incidence location and incidence type. The definition of incidence type and examples of incidence location are presented in Appendix Table A2.

Figure B15: Impact of pension payday on ambulance transport by age group and gender

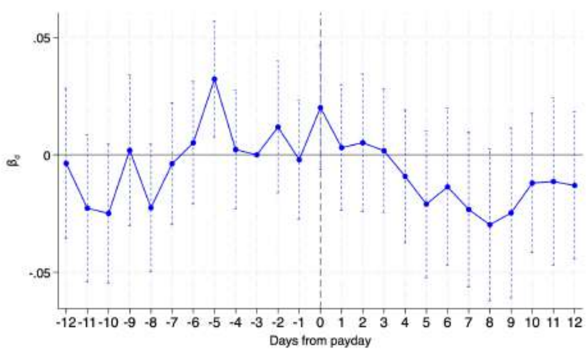
(a) Female, 65-69



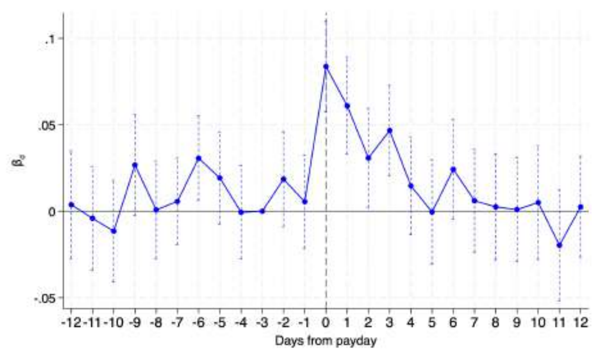

(b) Female, 70-74



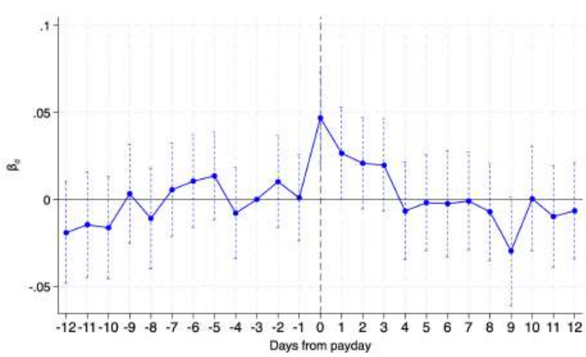

(c) Female, 75-79



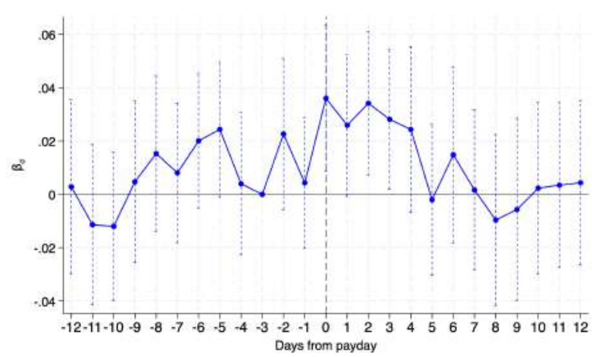

(d) Male, 65-69




(e) Male, 70-74



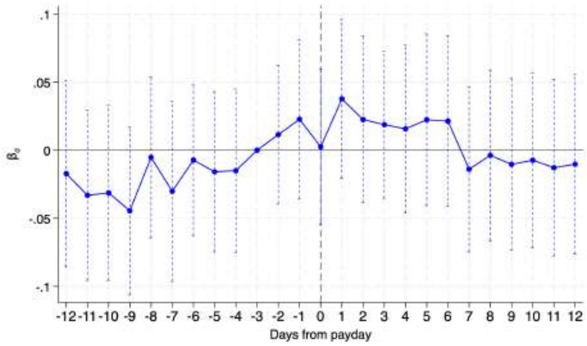

(f) Male, 75-79



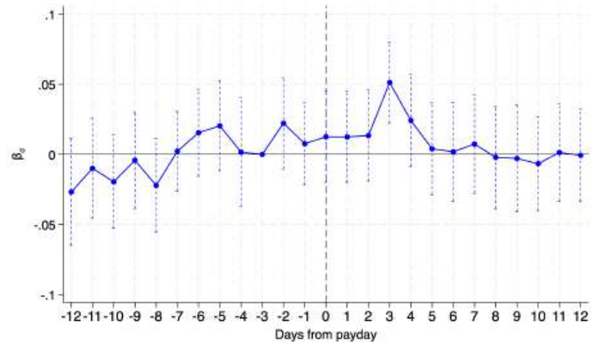

*Notes*: This figure shows the coefficient estimates of $\beta_d$, where $d = \{-12, -13, ..., -1, 0, 1, ..., 12\}$ from Equation (1), using all the ambulance transport data between 2007 and 2019. The number of observations is 3,900. The dotted bar shows the 95 percent confidence interval. $d = 0$ shows the payday. The coefficient estimates show the difference in the relative increase in ambulance transport cases compared to the reference day, three days before the payday, between payment and nonpayment months.

Figure B16: Impact of pension payday on the ambulance transport by severity

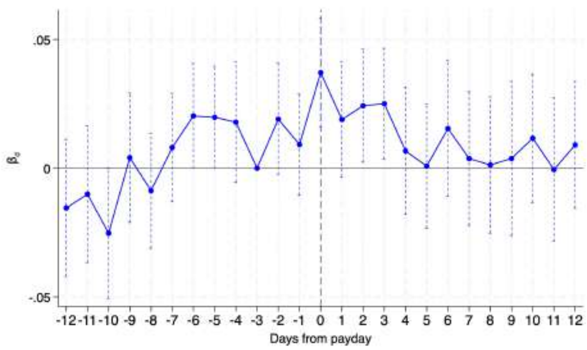
(a) Fatal/Death



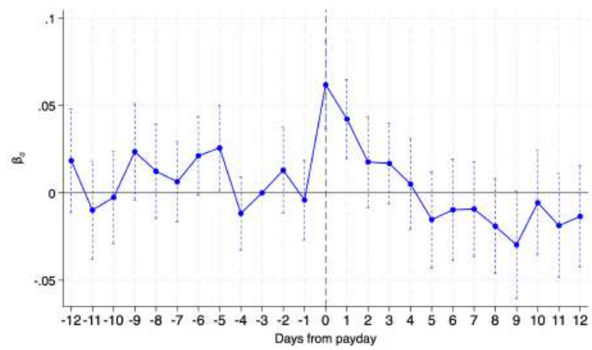

(b) Serious




(c) Severe



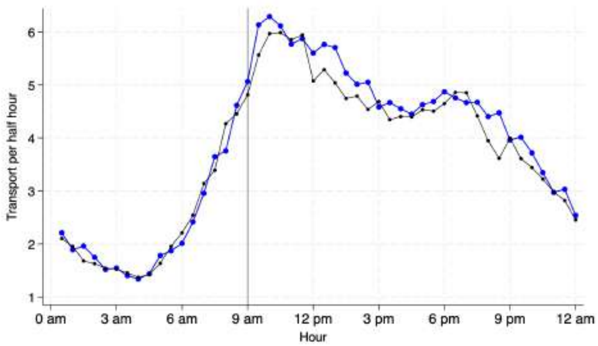

(d) Modest



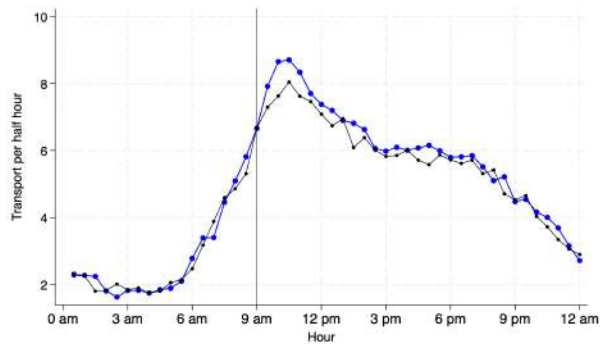

*Notes*: This figure shows the coefficient plot of $\beta_d$, where $d = \{-12, -13, ..., -1, 0, 1, ..., 12\}$ from Equation (1), using all the ambulance transport data between 2007 and 2019. The number of observations is 3,900. The dotted bar shows the 95 percent confidence interval. $d = 0$ shows the payday. The numbers show the difference in the relative increase in ambulance transport cases between payment and nonpayment months. The reference day is three days before the payday. The definition of severity is presented in Appendix Table A2.

Figure B17: Ambulance transport by half-hour on the payday by gender and age group

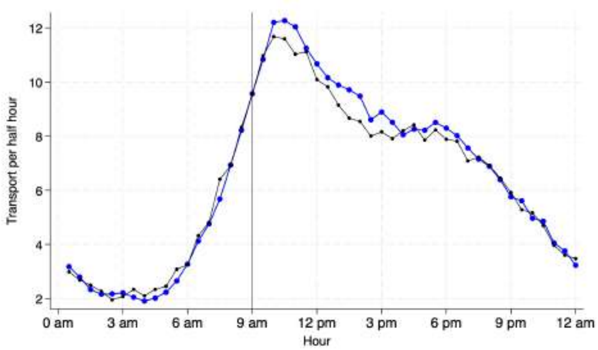
(a) Female, 65-69



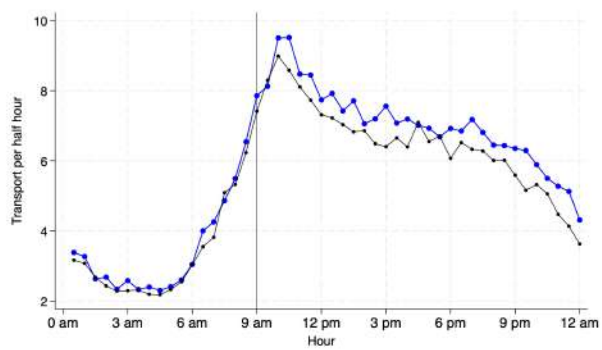

(b) Female, 70-74



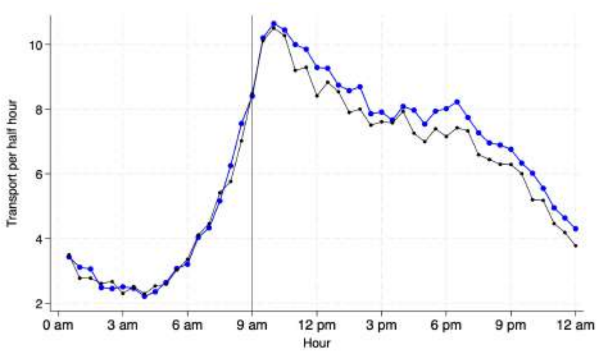

(c) Female, 75-79



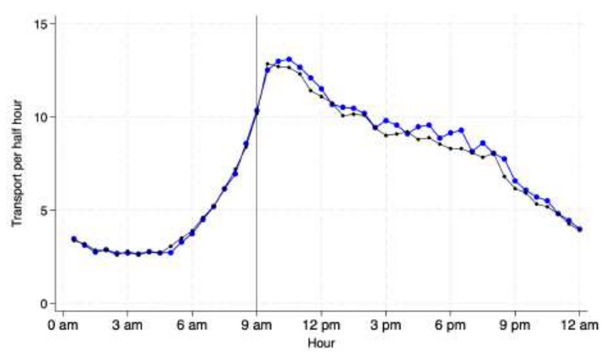

(d) Male, 65-69




(e) Male, 70-74



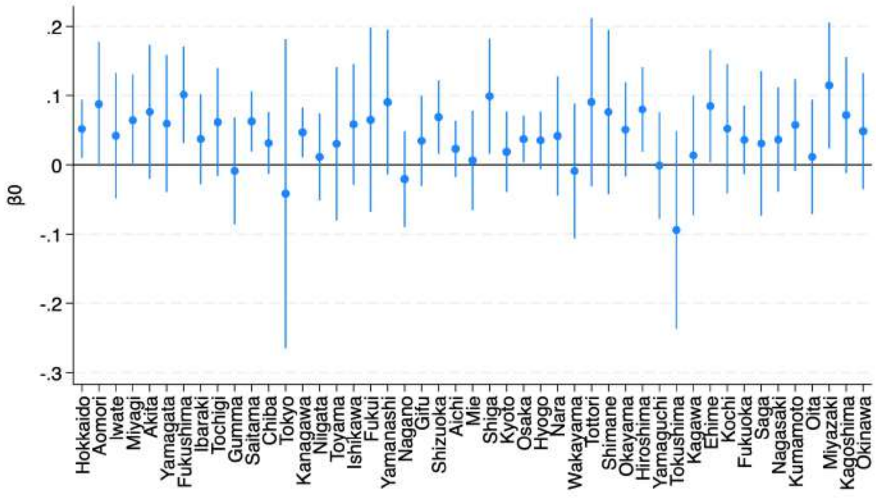

(f) Male, 75-79



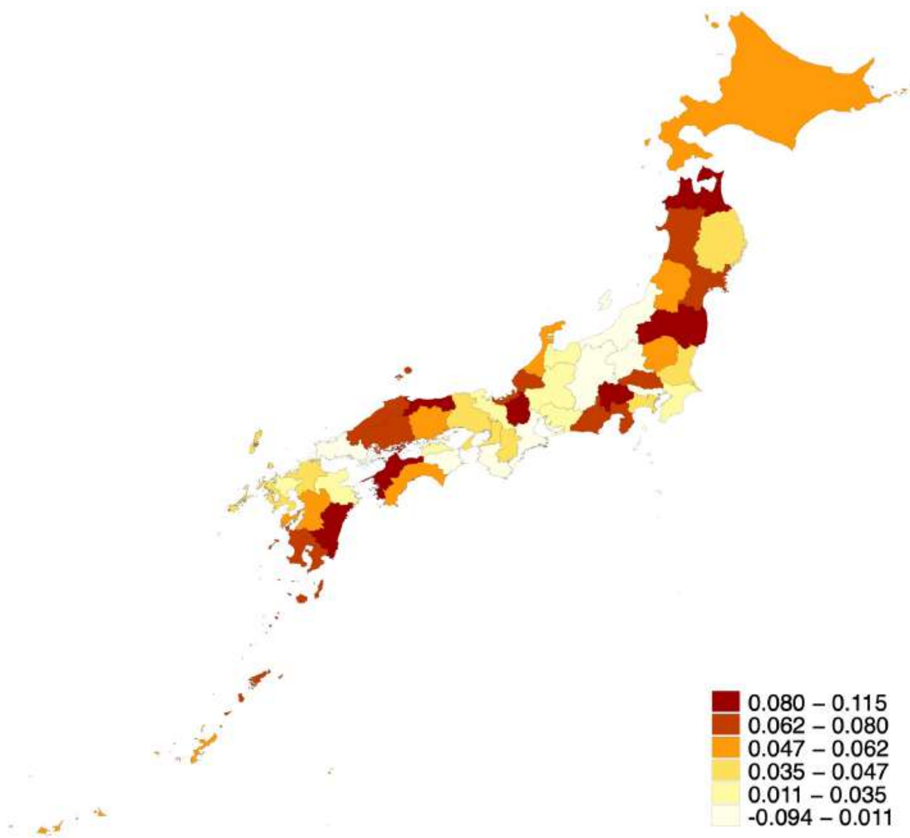

*Notes*: This figure shows the plot of the average number of ambulance transport cases in each 30 minute bin over the sample period, 2007 to 2019, for each age gender group. In each panel, there are two lines. The blue line shows payment months, and the black line shows nonpayment months. The vertical line represents 9:00 am.

Figure B18: Impact of pension payday on ambulance transport by prefecture

(a) Coefficient estimates

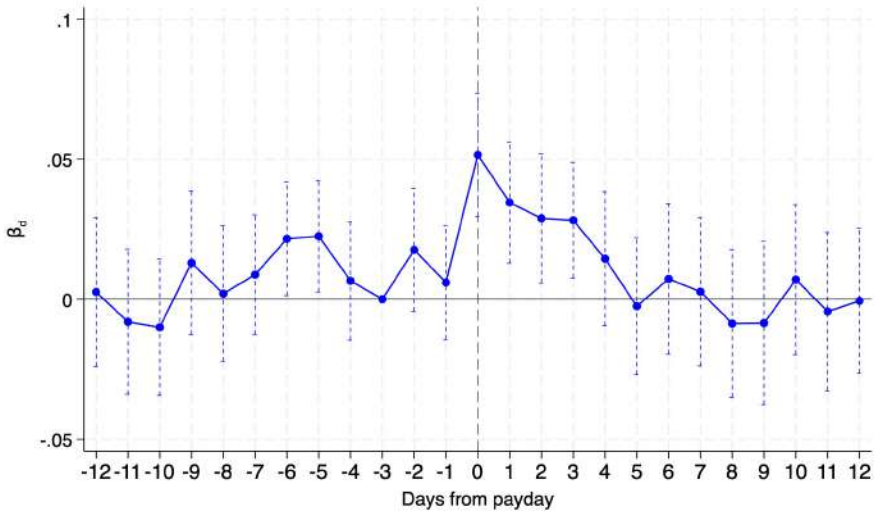



(b) Geographical representation




*Notes*: This figure shows the coefficient plot of $\beta_0$ of Equation (1), using the ambulance transport data between 2015 and 2019. In Panel (a), the bar shows the 95% confidence interval. The number of observations is 3,900. The numbers show the difference in the relative increase from the reference day in ambulance transport cases between payment and nonpayment months. The reference day is three days before the payday.

Figure B19: Triple-difference analysis



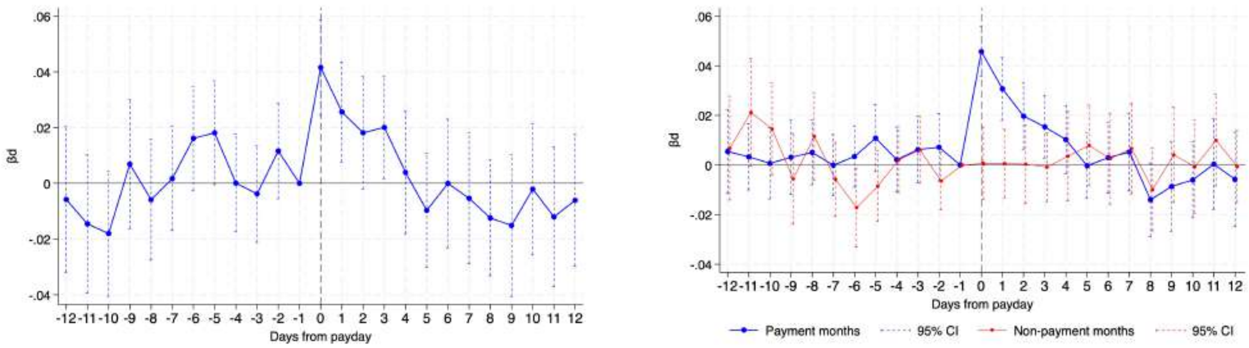

*Notes*: This figure shows the coefficient plot of interest in the triple-difference regression analysis, where the additional difference by age group (65-79 and 55-59) is added to the analysis. The number of observations is 3,900. The dotted bar shows the 95 percent confidence interval. $d = 0$ shows the payday. The reference day is three days before the payday.

# C Robustness check 1: An alternative reference day

Figure C1: Impact of pension payday on ambulance transport

(a) Difference in difference analysis

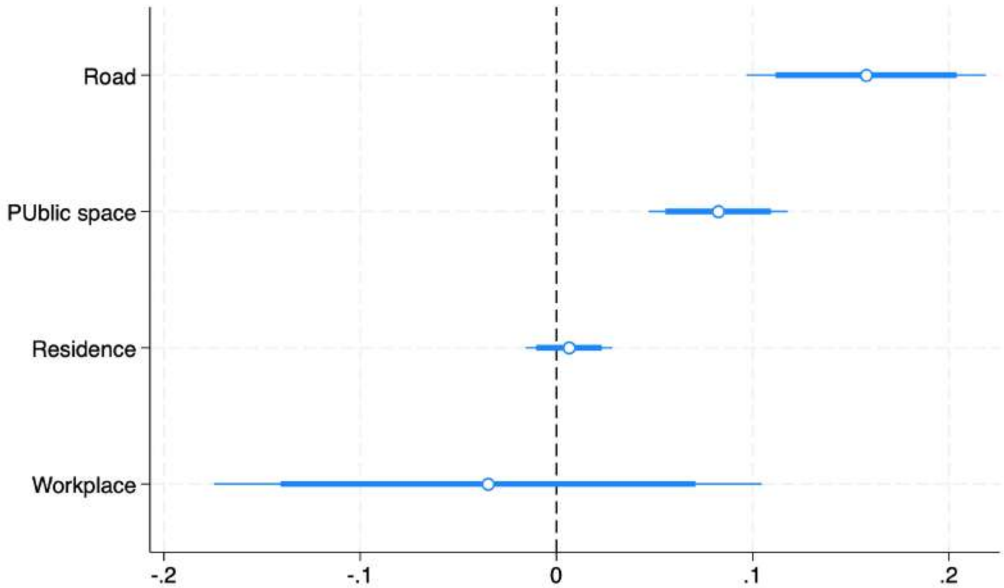
(b) Payment months and non-payment months



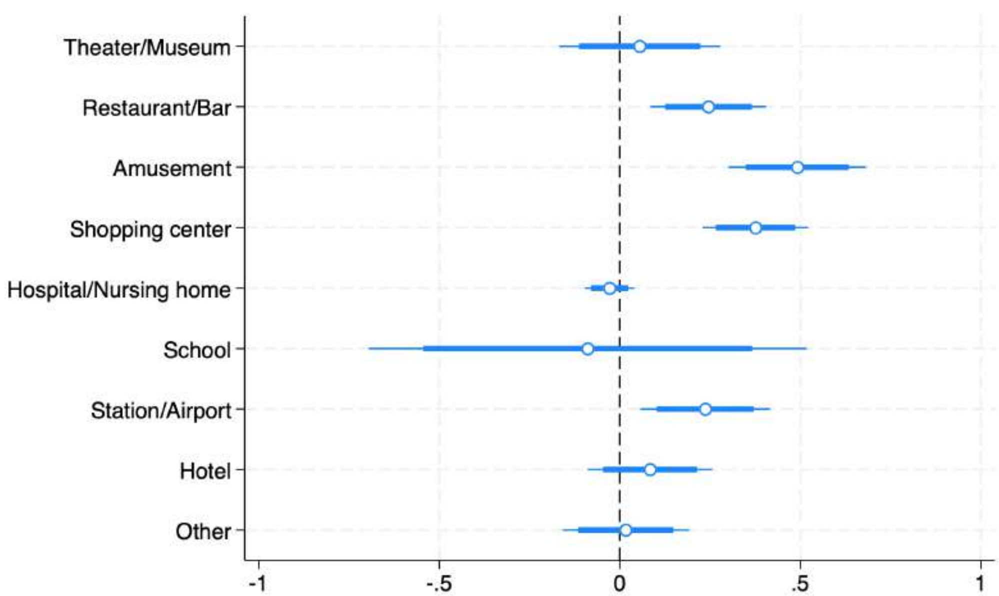

*Notes*: Panel (a) shows the coefficient plot of $\beta_d$, where $d = \{-12, -13, ..., -1, 0, 1, ..., 12\}$ from Equation 1, using all the ambulance transport data between 2007 and 2019. The number of observations is 3,900. The dotted line shows the 95 percent confidence interval. $d = 0$ shows the payday. The numbers show the difference in the relative increase in ambulance transport cases between payment and nonpayment months. Panel (b) shows the change in ambulance transport cases on each day of the synthetic month from the one day before the payday in payment and nonpayment months, using all the ambulance transport data between 2007 and 2019. The number of observations is 1,950. The dotted bar shows the 95 confidence interval. $d = 0$ shows the payday for payment months and the corresponding day for nonpayment months. The blue line shows payment months, and the red line shows nonpayment months. The numbers show an increase in ambulance transport cases compared to one day before the payday.

Figure C2: Impact of income receipt on ambulance transport on the payday and five-day average of the impact by incidence location

(a) Large category



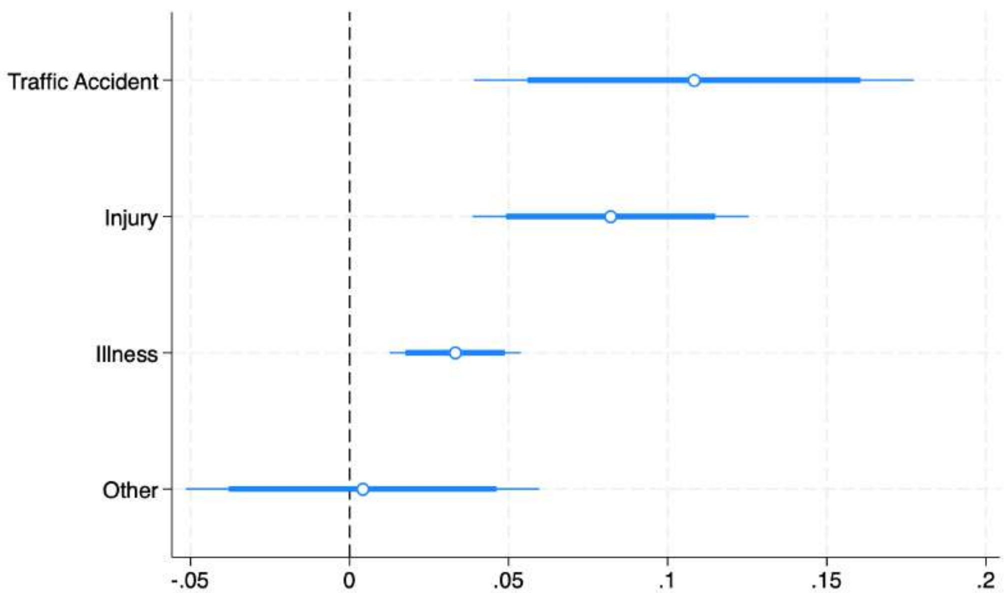

(b) Public space



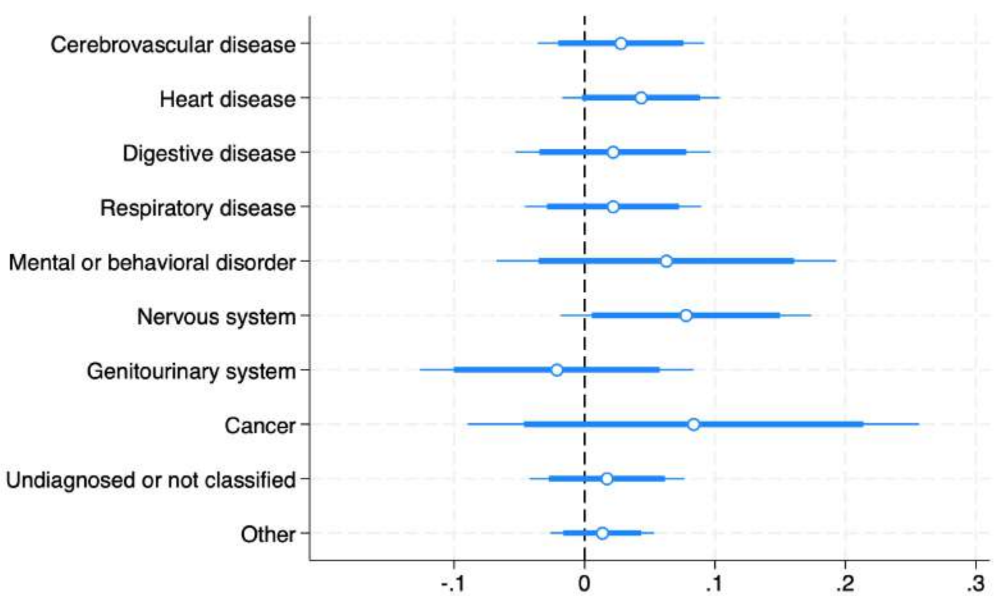

*Notes*: This figure shows the coefficient plot of $\beta_0$ of Equation (1) using all the ambulance transport data between 2007 and 2019 for Panel (a) and between 2015 and 2019 for Panel (b). For Panel (a), the number of observations is 3,900. For Panel (b), the number of observations is 1,500. The thin bar shows the 99% confidence interval, and the thick bar shows the 95% confidence interval. The numbers show the difference in the relative increase from the reference day in ambulance transport cases between payment and nonpayment months. The reference day is three days before the payday. The examples of each location category are presented in Appendix Table A2.

Figure C3: Impact of income receipt on ambulance transport on the payday and five-day average of the impact by incidence type and diagnosis

(a) Incidence type

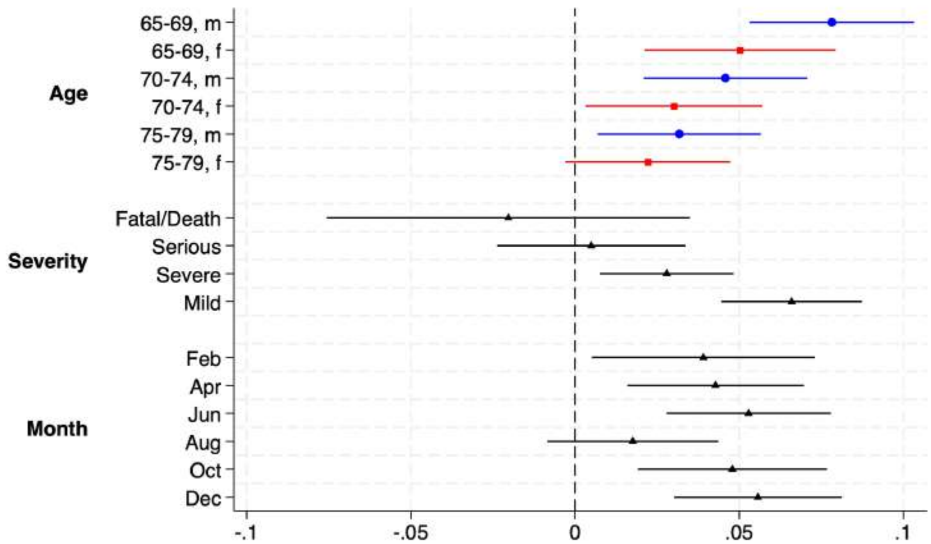



(b) Diagnosis for illness




*Notes*: This figure shows the coefficient plot of $\beta_0$ of Equation (1), using all the ambulance transport data between 2007 and 2019 for Panel (a) and between 2015 and 2019 for Panel (b). For Panel (a), the number of observations is 3,900. For Panel (b), the number of observations. The thin bar shows the 99% confidence interval and the thick bar shows the 95% confidence interval. The numbers show the difference in the relative increase from the reference day in ambulance transport cases between payment and nonpayment months. The reference day is three days before the payday. The definition of each incidence type and diagnosis category is presented in Appendix Table A2.

Figure C4: Heterogeneous impact by age and gender, severity, and month

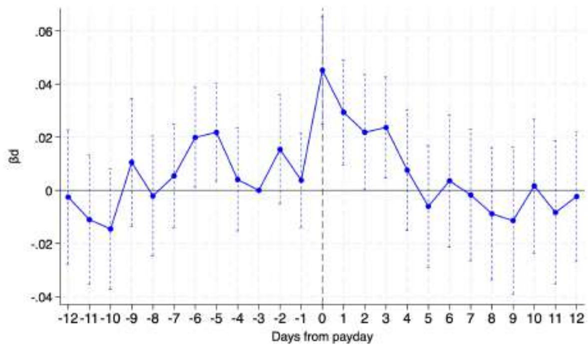



*Notes*: This figure shows the coefficient plot of $\beta_0$ of Equation (1) using the ambulance transport data between 2007 and 2019. The number of observations is 3,900 for the analysis by age and severity and 2,275 for the analysis by month. The bar shows the 95% confidence interval. The numbers show the difference in the relative increase from the reference day in ambulance transport cases between payment and nonpayment months. The reference day is three days before the payday. Blue color shows males, and red color shows females. Three age groups are analyzed: 65-69, 70-74, and 75-79. The definition of severity is presented in Appendix Table A2.

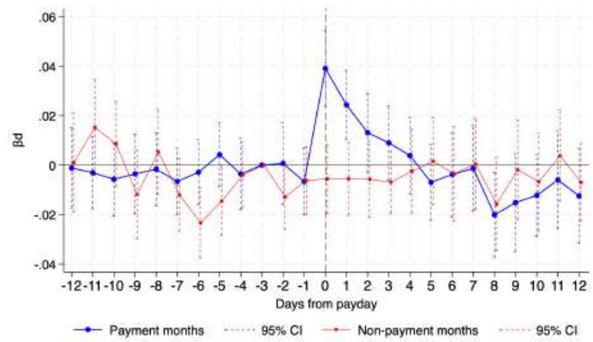
# D Robustness check 2: Year-month fixed effect

Figure D1: Impact of pension payday on ambulance transport

(a) Difference in difference analysis



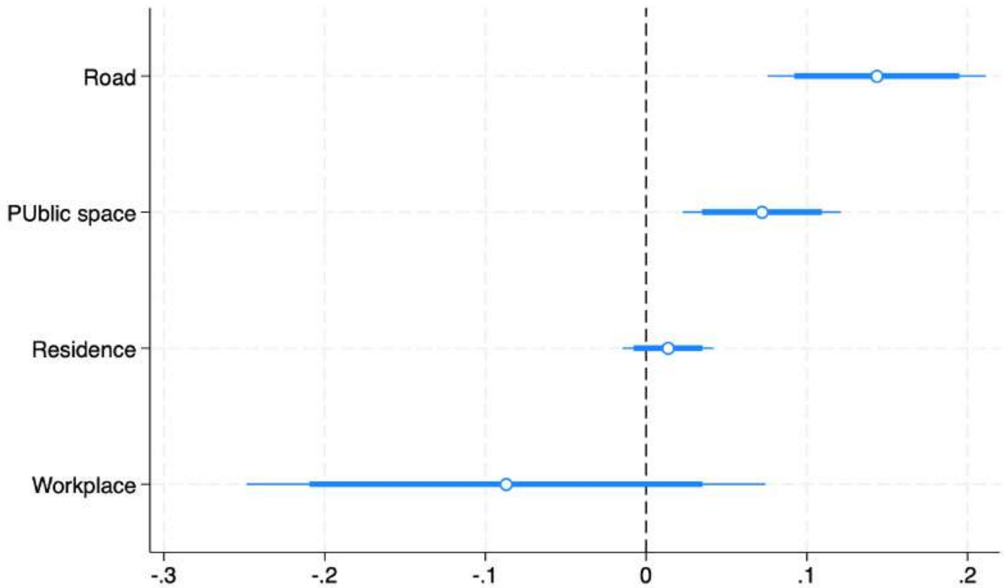

(b) Payment months and non-payment months



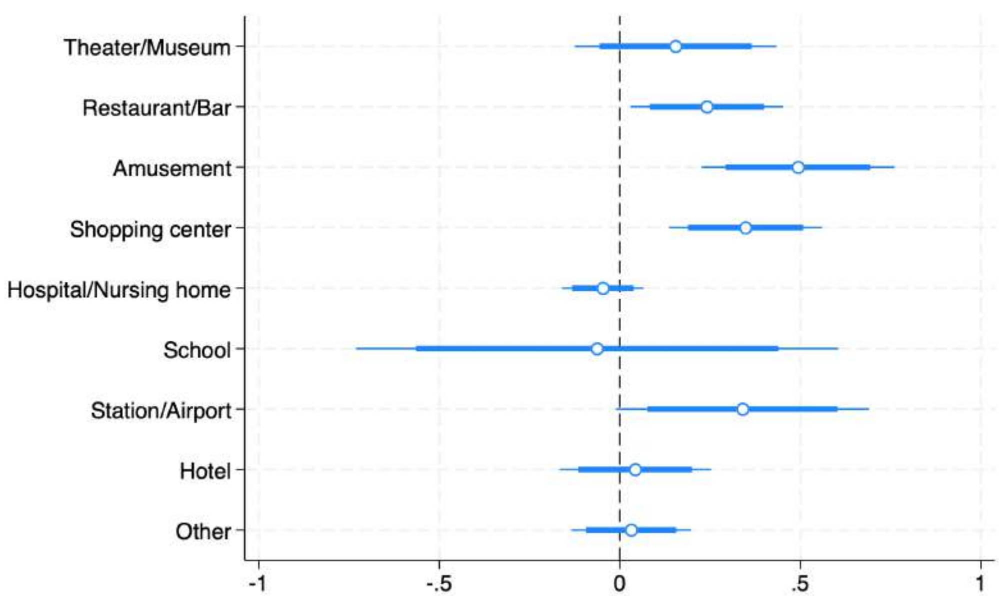

*Notes*: Panel (a) shows the coefficient plot of $\beta_d$, where $d = \{-12, -13, ..., -1, 0, 1, ..., 12\}$ from Equation (1) with the year and month fixed effects replaced by the year-month fixed effect, using all the ambulance transport data between 2007 and 2019. The number of observations is 3,900. $d = 0$ shows the payday. The numbers show the difference in the relative increase in ambulance transport cases between payment and nonpayment months. Panel (b) shows the change in ambulance transport cases on each day of the synthetic month from the three days before the payday in payment and nonpayment months, using all the ambulance transport data between 2007 and 2019. The dotted bar shows the 95 confidence interval. $d = 0$ shows the payday for payment months and the corresponding day for nonpayment months. The blue line shows payment months, and the red line shows nonpayment months. The numbers show an increase in ambulance transport cases compared to three days before the payday.

Figure D2: Impact of income receipt on ambulance transport on the payday and five-day average of the impact by incidence location

(a) Large category



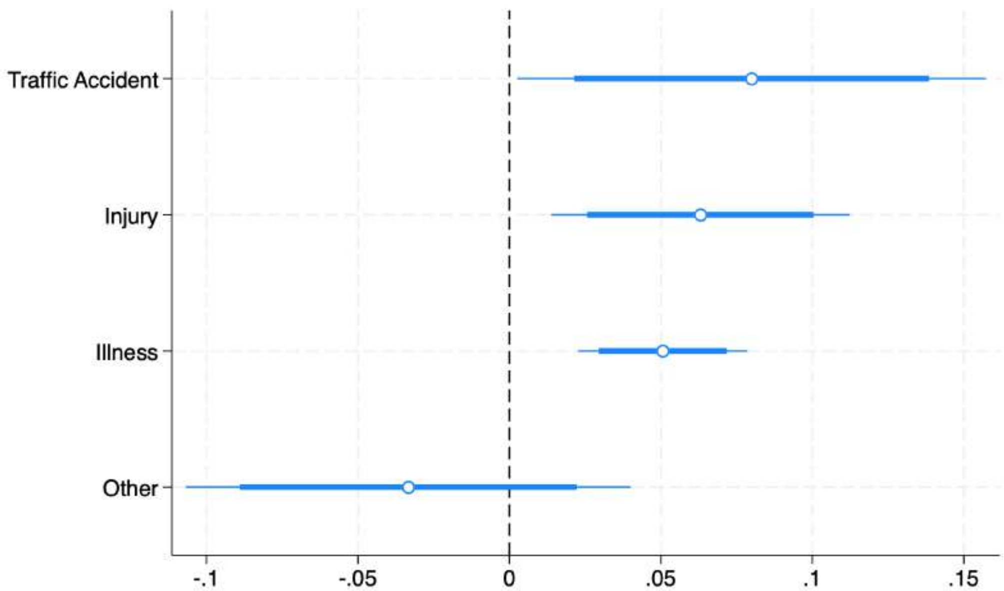

(b) Public space



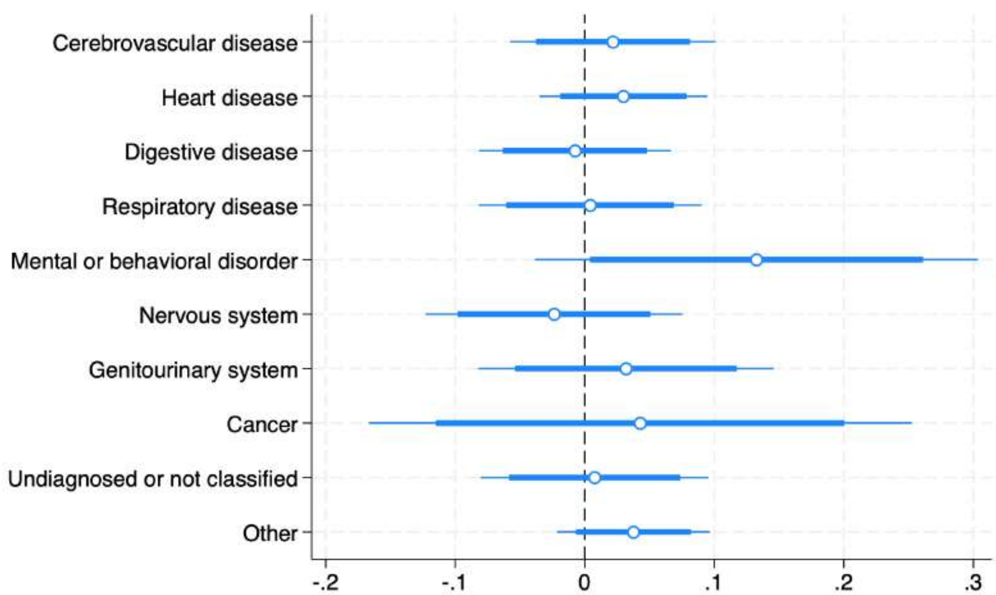

*Notes*: This figure shows the coefficient plot of $\beta_0$ of Equation (1) with the year and month fixed effects replaced by the year-month fixed effect, using all the ambulance transport data between 2007 and 2019 for Panel (a) and between 2015 and 2019 for Panel (b). For Panel (a), the number of observations is 3,900. For Panel (b), the number of observations is 1,950. The thin bar shows the 99% confidence interval, and the thick bar shows the 95% confidence interval. The numbers show the difference in the relative increase from the reference day in ambulance transport cases between payment and nonpayment months. The reference day is three days before the payday. The examples of each location category are presented in Appendix Table A2.

Figure D3: Impact of income receipt on ambulance transport on the payday and five-day average of the impact by incidence type and diagnosis

(a) Incidence type

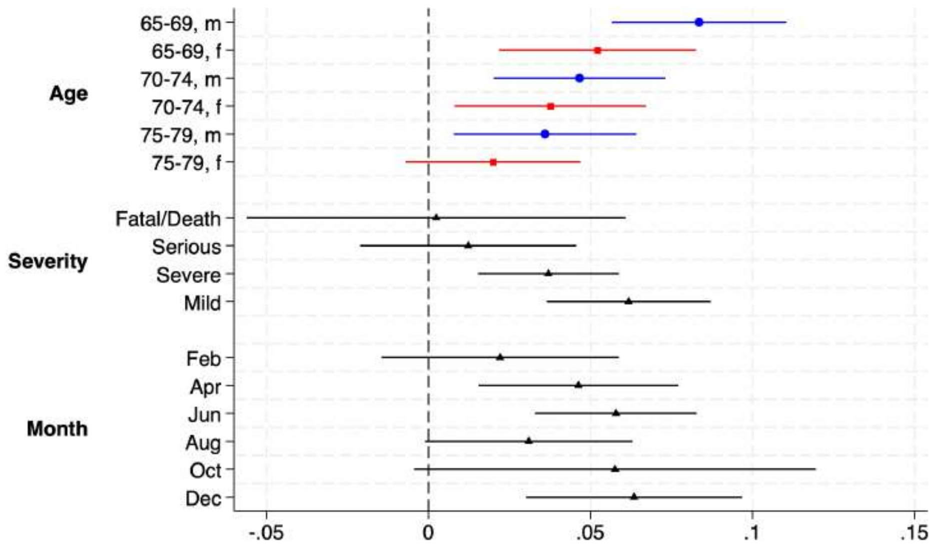



(b) Diagnosis for illness




*Notes*: This figure shows the coefficient plot of $\beta_0$ of Equation (1) with the year and month fixed effects replaced by the year-month fixed effect in the right panel, using all the ambulance transport data between 2007 and 2019 for Panel (a) and between 2015 and 2019 for Panel (b). For Panel (a), the number of observations is 3,900. For Panel (b), the number of observations is 1,500. The thin bar shows the 99% confidence interval, and the thick bar shows the 95% confidence interval. The numbers show the difference in the relative increase from the reference day in ambulance transport cases between payment and nonpayment months. The reference day is three days before the payday. The definition of each incidence type and diagnosis category is presented in Appendix Table A2.

Figure D4: Heterogeneous impact by age and gender, severity, and month




*Notes*: This figure shows the coefficient plot of $\beta_0$ of Equation (1) with the year and month fixed effects replaced by the year-month fixed effect in the right panel using the ambulance transport data between 2007 and 2019. The number of observations is 3,900 for the analysis by age and severity and 2,275 for the analysis by month. The 95% confidence interval. The numbers show the difference in the relative increase from the reference day in ambulance transport cases between payment and nonpayment months. The reference day is three days before the payday. Blue color shows males, and red color shows females. Three age groups are analyzed: 65-69, 70-74, and 75-79. The definition of severity is presented in Appendix Table A2.