# Household Penalty*

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**Abstract**

This paper examines how spousal health shocks affect gender disparity in health and labor outcomes. We define "household penalty" as the burden on family members resulting from other members' health issues. We use data from US insurance claims and Mexican labor surveys to explore the unequal penalty placed on women. In the US, a difference-in-difference analysis shows that partners' infection increases their own infection probabilities by 1.2 pp (percentage points) for males and 2.2 pp for females. In Mexico, women's probability of illness increases by 11 pp, and labor supply decreases by 4.6 hours following their male partner's health shock. This effect for men is a 3-hour labor reduction and a 3.8 pp increase in infection likelihood. The key mechanism lies in household specialization: as women's income share increases, their penalty decreases, while men's penalty increases. Our findings highlight the important role of informal caregiving in reinforcing health and labor market gender disparities.

JEL Classifications: I14, J22, O12, O15
Keywords: Household disease transmission, gender, home production, labor supply

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# 1 Introduction

Within households, agents frequently engage in interactions that give rise to externalities, many of which bear significant implications for overall welfare. A salient example of such an externality is the transmission of health shocks. Here, a negative health event affecting one agent can precipitate a series of repercussions on the health, productivity, and labor supply decisions of other household members (Daysal et al., 2021). This phenomenon offers a unique perspective for analyzing intra-household resource allocation, especially under the lens of infectious disease transmission and its consequences for health outcomes.

This framework of health-related externalities is intricately linked to the gender dynamics within households, particularly emphasizing the role of women as primary caregivers. Women are inherently subject to distinct health challenges, influenced by biological factors, economic barriers, and societal norms. In this context, their often-assumed caregiving roles—rooted in social expectations and economic constraints—further exacerbate their vulnerability to health shocks.

Building on these themes, our paper delves into the interaction between intra-household health shock externalities and gender-based health and economic disparities. We investigate whether female agents, vis-a-vis their male counterparts, incur a disproportionate health and economic cost when another agent within the household experiences a health shock. By analyzing the responses of female health conditions and labor supply decisions to these shocks, we aim to shed light on the economic mechanisms driving these outcomes.

We introduce a concept of "household penalty", defined as the spillover effect of family members' health shocks on other members' health conditions and labor outcomes. Focusing on infectious disease transmission, we build a theoretical framework of the health production model as an extension of Grossman (2000). We assume an individual's health depends on their previous health stock and other family members' investment, which is a household optimization problem. Due to the negative impact of providing care to an infected family member on the caregiver's health, our model derives optimal caregiving time allocated by male and female members. We calculate gender-specific caregiving time and equilibrium health outcomes. Females face extra penalties if they have comparative advantages in providing care or have lower incomes than male members.

We test household penalties in two empirical settings. First, we use insurance claims data in the US. With detailed and matched information on patient-level claims and household-level characteristics, we quantify the higher probability of getting infected under the condition of an earlier infection of a family member, i.e., the household penalty, and we reveal how this penalty differs by gender. Under a difference-in-difference design, we find the probability of infection is 1.2 percentage points higher for male members and 2.2 percentage points higher for female members due to household contagion, namely 12.4% and 22.7% higher relative to the average infection rate. The results are robust after controlling for household size, household income,

home value, and the number of children and adults in the household. Disentangling the effect by member's gender, we find no significant evidence of male-to-male transmission, while male-to-female and female-to-male transmission increases the exposed individual's infection rate by 2.8 and 1.5 percentage points. Extra household penalty for females is more striking when the first infected patient is middle-aged and in areas with a striking gender gap in income and in home production intensity.

Building upon insurance claims data, our study furthers the analysis through the Mexican Labor Survey (ENOE) which allows us to additionally examine the labor outcomes and delve into the mechanisms. This dataset encompasses approximately 17,000 dual-worker households, and has a 5-period rotating panel structure. Contrary to the insurance claims data, it is representative of the population and covers both formal and informal employment. Our empirical strategy parallels that employed for insurance claims, with the interaction between the female gender and having a sick partner serving as the estimator for the extent of the female penalty. We primarily anchor our analysis on two dependent variables: the likelihood of an individual abstaining from work in the preceding week due to sickness or personal reasons, and the cumulative working hours during the same period. The results show that a male partner's sickness triggers an 11-percentage-point increase in the probability of their female counterpart also being sick, a stark contrast to the 3.8 percentage point rise for males when the scenario is inversed. Regarding labor hours, sick male partners precipitate a 4.6-hour reduction in females' work, while males curtail their hours by 3 when faced with a sick female partner. Cumulatively, the findings underscore a salient gender asymmetry, wherein females grapple with a more profound health and labor penalty in the wake of their partner's health setbacks. Our findings are robust to the inclusion of control variables such as age, survey time, state, municipality, and individual-specific fixed effects.

Our heterogeneity analysis demonstrates that the presence of other potential caregivers can insulate women from the household penalty. When an elderly female, potentially serving as an alternate caregiver, is present in the household, the female health spillover effect from a male partner's sickness reduces by 1.5 percentage points.

Moreover, the results from the Mexican data confirm the model's predictions regarding the role of income composition within the household. Transitioning from a male-only earner household to a female-only earner household eradicates the added female penalty in falling sick. Moreover, in households where women are the primary earners, men cut back on their work hours more when their female counterparts face health challenges. This observation aligns with the notion that household specialization acts as a key mechanism in driving the gender disparity in household penalty.

Another mechanism lies in the uneven burden of home production faced by female members, such as in housework and childcare. We use time-use survey data and find particularly pronounced gender disparities in areas with more substantial gender gaps in home production time. Females tend to shoulder a greater share of the housework burden compared to their partners. In the

context of infectious diseases, females' significant caregiving contributions may be implicitly expected, necessitating their provision of care to infected patients.

Our paper provides a novel empirical investigation into gender inequality in household health spillovers. We examine how partners' transmittable infections affect the health and labor supply decisions of other household members. Previous epidemiological studies have primarily focused on health spillovers, highlighting the disproportionate infection rates among females due to household transmission. For instance, Nkangu et al. (2017) reported a higher incidence of Ebola cases among women compared to men, despite the absence of a biological gender vulnerability gap. They suggested that women's primary role as caregivers in households might be a contributing factor but did not provide numerical evidence to support this claim. Similar assertions can be found in the works of WHO (2007) and Skrip et al. (2017), which emphasize gendered roles in domestic work and the varying infection risks associated with these roles within households. Close to our study is Daysal et al. (2021), which focuses on the disease transmission across young children within a family and the implications for their future outcomes, and Arrieta and Li (2023), which analyses family members' employment responses following an ED visit in the US context. Complementing this work, our paper concentrates on the household transmission of infections among adult members driving the gender gap in health and labor supply in both developed and developing countries.

This study extends the current understanding of the determinants of female labor supply by elucidating the disproportionate impact of partners' health shocks on women's labor decisions. Existing papers in this field primarily emphasize factors such as childbirth and childcare (Kleven et al. (2019); Aguilar-Gomez et al. (2019)). However, the existing body of literature concerning caregiving to adults and its implications on the labor market predominantly addresses elderly care (Mommaerts and Truskinovsky, 2020, 2023) or care for adults with serious or permanent disabilities (Fadlon and Nielsen, 2019, 2021; Lee, 2020; Brito and Contrera, 2023). An exception in this context is the study by Maestas et al. (2023), which investigates the long-term labor market effects of caregiving on different age groups. These studies, however, are primarily confined to developed countries or focus only on formal employment responses. We add to this literature by analyzing responses to common, transient infectious diseases among working-age adults in both formal and informal sectors. Our study reveals substantial asymmetries in the health and labor outcomes of female versus male caregivers following the health shock.

Moreover, in addition to the analysis in the US setting, we complement previous literature by looking at a developing country (Mexico). In developing countries like Mexico, characterized by a substantial informal employment sector and pronounced gender norms, the repercussions of household health shocks on the labor supply are potentially more pronounced. By incorporating a representative sample including both formal and informal employment, our paper offers a comprehensive perspective on how household health shocks can disproportionately affect health and labor supply outcomes, thereby contributing to gender disparities.

Empirics aside, our paper is the first to apply infectious disease to the Grossman model of

health production. Infectious disease provides a novel setting where initial health shocks affect exposed family members' health through two channels: the direct effect of being infected on health conditions, and the indirect effect through the income channel due to decreased time on labor supply. In contrast, existing literature on health production mostly focuses on non-infectious initial shocks that affect others' health through the indirect income channel (e.g., Yi et al., 2015; Barreca et al., 2016; Heckman et al., 2018). Additionally, we separately discuss the equilibrium across the severity of infectious disease. Our main model focuses on the optimal care-providing time and health conditions when the infectious disease does not pose an excessively high risk and the provision of care yields sufficient returns. In Section S1, we explore an extreme scenario where the infectious disease is highly transmittable, the cost of care provision is high, the optimal caregiving amount is zero, and external interventions are needed to enhance public health. This has real-world implications like pandemics and vaccination investment.

From the policy perspective, our paper highlights the pressing need for intensified efforts in health support and infectious disease prevention. The consequences of health burdens are not confined solely to an individual's health status but rather ripple through to impact family members' health and labor outcomes. Consequently, our paper underscores the critical importance of prioritizing preventive measures to mitigate the far-reaching socioeconomic effects of health crises.

Furthermore, this paper underscores the need of implementing supportive policies aimed at benefiting female family members. Our findings show that when partners become ill, females bear a disproportionate burden, grappling with heightened health-related challenges, caregiving responsibilities, and exacerbated adverse labor outcomes. To rectify this inequity, it is important to undertake proactive measures, including the provision of paid leave options for female caregivers or care subsidies.

The rest of the paper is structured as follows. Section 2 describes the background and related literature. Section 3 shows a stylized model that motivates our empirical study. Section 4 describes the data. Section 5 shows the empirical strategy, main results, and additional results using the US insurance claim data. Section 6 provides additional results using survey data from Mexico. Section 7 concludes.

# 2 Background

## 2.1 Related literature: household disease transmission

Intra-household transmission accounts for a great proportion of the spread of infectious diseases such as Ebola (Glynn et al., 2018) and COVID (Chan et al., 2020). Some epidemiological studies quantify the transmission rate among family members. For example, Curmei et al. (2020) estimate the household secondary attack rate of COVID, defined as the average number of within-household infections caused by a single index case, is 5-35% before social distancing

and 30-55% afterward. They conclude that household transmission is an effective target for COVID interventions. Other studies using different samples find lower household secondary attack rates, e.g., 5.2% by Yung et al. (2020) and 16.3% by Li et al. (2020). Due to different within-household transmission patterns, Esteve et al. (2020) show preventing primary infections of COVID among the elderly is most effective in countries with small households and little intergenerational coresidence, whereas confining younger age groups can have a greater impact in countries with large and intergenerational households. They confirm it is crucial to take household transmission into account so as to control the disease spread. Moreover, Daysal et al. (2021) demonstrate that within-household transmission to children can have critical long-term consequences in terms of human capital formation and earnings. Despite the importance of transmission within a family, little is known about the unequal exposure of family caregivers. As the burden of infectious disease has fallen since 1890, Goldin and Lleras-Muney (2018) find women benefit more greatly from this public health improvement. They mention one possible reason is that female children had a greater role in taking care of sick family members, whereas the boys were out of the house more, possibly at work.

Gender, together with other covariates, is shown to be associated with different exposure, infection, attitude, and response towards infectious diseases. Lewandowski et al. (2020) suggest women are more likely to be exposed to contagion due to their sectoral segregation into occupations that require more interpersonal interactions. They show that gender is a more important factor in workers' exposure than education or age. Similar results are found by Chernoff and Warman (2020). They show that mid-educated females are at the highest risk of infection among automatable jobs, mainly because they work in healthcare, office and administrative support and protective service occupations. When it comes to attitude and avoidance behaviors, Galasso et al. (2020) find women are more likely to see COVID as a very serious health problem, to agree with restraining public policy measures adopted in response to it, and to comply with them. Also, Papageorge et al. (2020) finds females are more likely to engage in self-protective behaviors and believe in the effectiveness of social distancing than males. These studies suggest that there is a natural gender difference in infection rate regardless of household transmission.

Infectious disease contributes to gender inequality. Earlier pandemics have been shown to increase gender gaps in schooling and education attainment (Archibong and Annan, 2017, 2020). On COVID, most studies discuss how the pandemic affects females' performance in the workplace and burden in housework. COVID increases the demand for home childcare and women have been doing the great share (Sevilla and Smith, 2020). Mothers spend substantially longer on housework and sacrifice a larger fraction of their paid work hours than their partners (Andrew et al., 2020). As a result, women are more likely to lose jobs than men due to COVID, and those still employed are more likely to work from home with disruptions and distractions (Farre et al., 2020; Papanikolaou and Schmidt, 2020).

Another aspect of gender inequality comes from mental health and utility of working in the presence of others. Gimenez-Nadal et al. (2020) find women benefit more from working with

others in their daily activities than do men. As a result, solo work due to COVID has more negative impacts on women's well-being. Survey evidence among prolific participants in the UK shows women are more concerned about getting and spreading the virus, perceive the virus as more prevalent and lethal, are more likely to expect a new lockdown or outbreak wave, and are more pessimistic about the current and future economy (Oreffice and Quintana-Domeque, 2020). Furthermore, it is widely discussed that COVID and related lockdowns increase domestic violence (e.g., Ravindran and Shah, 2020; Leslie and Wilson, 2020), which further worsens gender inequality.

### 2.2 Related literature: labor supply and household caregiving

The interplay between household caregiving and employment has been reviewed by Lilly et al. (2007) and Bauer and Sousa-Poza (2015). The impact of informal caregiving on employment remains a topic of debate within the literature with mixed results. Brito and Contrera (2023) shows that adult daughters' employment decreases by 3% following their elderly parent's cancer diagnosis, while sons' employment remains unaffected. Maestas et al. (2023) find similar magnitudes for female caregivers under 50, which lasts for about 5 years, while men experience a decline in employment before the caregiving episode, and the recovery takes considerably longer. Fadlon and Nielsen (2021) use Danish administrative data to demonstrate that non-fatal, severe shocks to a spouse's health do not affect employment responses, as the formal insurance fills the missing income. Lee (2020) find no impact on female weekly working hours following husband's disability, but a 2-3 hour's increase in time spent on providing care. Coile et al. (2022) shows that negative impact on female employment can be mitigated by access to paid family leave. Arrieta and Li (2023) reveals an increase in female working hours by 0.5% following a family member's visit to the ED, while no impact on men, consistently with the insurance mechanism dominating the caregiving mechanism. They also show that the increase in labor supply is less pronounced for conditions requiring more caregiving. It's important to note that many of these dynamics, including formal insurance and paid family leave, are predominantly characteristic of affluent, developed nations. Consequently, the nature of these problems and their responses are likely to vary substantially in different socio-economic contexts. More substantial effects have been observed in cases of very intense caregiving. When caregiving responsibilities exceed ten hours per week, caregivers tend to allocate fewer hours to the labor market compared to non-caregivers (Lilly et al., 2007). Moreover, intense caregiving is predominantly undertaken by working-age females, who are often less likely to be fully employed and typically earn lower wages (Bauer and Sousa-Poza, 2015).

The consequences of informal caregiving, such as reduced employment rates and shortened work hours, lead to significant productivity losses for both employed caregivers and their employers. In Spain, caregivers of individuals with Alzheimer's disease experienced an average reduction of seven hours per week, equivalent to one lost workday in the last month or nearly two partial workdays (Darbà and Kaskens, 2015). The quantified productivity loss varied based on the level

of impairment of the individuals with dementia (Gustavsson et al., 2011; Darbà and Kaskens, 2015; Michalowsky et al., 2016, 2018). For instance, a German study found higher monetary productivity losses in patients with mild and moderate cognitive impairment (Michalowsky et al., 2016, 2018). Additionally, in this German sample, caregivers' average weekly working hours decreased from 34 to 30 as the patients' cognitive impairments progressed. In Spain, the cost of productivity loss was estimated at 378 euros per month, although this figure included expenses related to the institutional setting, making direct comparisons challenging (Farré et al., 2018). A comparative study across Spain, Sweden, the United Kingdom, and the US, focusing on caregivers of community-dwelling Alzheimer's patients, revealed a substantial linear increase in productivity loss from mild to severe dementia, particularly evident in the Swedish sample (Gustavsson et al., 2011).

### 2.3 Institutional context in Mexico

Mexico provides a unique setting for our investigation into the interaction between health shocks and gender inequality, driven by several contextual factors.

First, Mexico's societal landscape is characterized by gender-based division of labor within households. Women traditionally bear a disproportionate burden of caregiving responsibilities (DiGirolamo and Salgado de Snyder, 2008), while men usually contribute a larger share of household income. These prevailing gender norms shape our inquiry, as they underlie gender inequality in income distribution and may contribute to disparities in the impact of partner's health shocks. Earlier studies noted that caregiving for the elderly often falls on female members of the household disproportionately.

Second, Mexico grapples with significant labor market informality (Aguilar-Gomez et al., 2019), which can be linked to a higher reliance on informal caregiving methods, such as within-household care. This informality is distinct from the United States, where formal healthcare is more prevalent. Understanding the dynamics of informality in Mexico is critical, as it might amplify the gender disparities in the consequences of spousal health shocks.

Moreover, Mexico exhibits pronounced occupational gender segregation, with women often concentrated in informal employment and sectors such as hospitality, which entail greater interpersonal interactions. This segmentation is relevant to our analysis as it can influence labor supply outcomes and the extent of reliance on household caregiving (World-Bank, 2019).

Additionally, the COVID pandemic has left an indelible mark on Mexico's economic landscape, intensifying the demand for caregiving and childcare due to lockdown measures. Globally, these responsibilities have disproportionately fallen on women, impacting their labor force participation and earnings (Alon et al., 2020). Our investigation seeks to disentangle the intricate interplay between spousal health shocks, traditional gender roles, healthcare disparities, and the informal labor market, all of which contribute to gender-based inequalities in the repercussions of health shocks.

# 3 Stylized Model

This study aims to explore household penalty, defined as the impact of a family member's infectious health shock on the health conditions and labor supply decisions of other household members. Our primary focus is the gender difference in household penalty.

We develop a one-period model of household health production based on Grossman (2000). Health depends on previous health stock and investment in this period. The former is taken as given, and the latter is a chosen level of optimization. Investment in health comes from care provided by an individual's family member. Health is a pure investment good and only indirectly affects utility through labor supply.

Computing household penalty relies on comparing the optimal decisions in infection-free households to the scenario where an infectious disease is present. We start by deriving optimal decisions for households without any infection. This serves as a benchmark. We then introduce an infectious disease into the household. In this new scenario, we re-evaluate the optimal responses of the household members to the presence of the infection. The *household* penalty is then quantified as the difference in outcomes between the infection-free benchmark and the scenario where the household is impacted by the infectious disease.

### Model setup

Assume that a representative household includes a male and a female member, and they jointly consume an aggregated consumption good $x_c$.[1] They jointly maximize their household utility:

$$U = U[x_c]$$

The budget constraint is a function of wage, caregiving time, and health promotion income:

$$x_c \leq w_m(T - C_m) + w_f(T - C_f) + P(H_m - \bar{H}_0) + P(H_f - \bar{H}_0)$$

where $w_m$ and $w_f$ are wage rate for male and female. $T$ is fixed total time endowments. $C_m$ and $C_f$ are time allocated to caregiving by male and female member, $1 \leq C_m \leq T$ and $1 \leq C_f \leq T$. Both of them get extra earnings if they have better health conditions, and the return rate is $P$. We have $w_m, w_f > 0$ and $P > 0$. The health production function is as follows:

$$H_m = \bar{H}_0 + \alpha ln C_f$$

$$H_f = \bar{H}_0 + \beta ln C_m$$

where $0 < \alpha < 1$, $0 < \beta < 1$. $\bar{H}_0$ is the same initial health stock for male and female. We assume care promotes health, and the marginal return of care is diminishing.

[1] We develop a family bargaining model in Appendix section S1.1.

The household's problem is to maximizing household utility through their choices of $C_m$ and $C_f$. This is equivalent to maximizing their household income. The first-order conditions are:

$$\left.\frac{\partial x_c}{\partial C_m}\right|_{C_m^*} = -w_m + \frac{\beta}{C_m^*}P = 0$$
$$\left.\frac{\partial x_c}{\partial C_f}\right|_{C_f^*} = -w_f + \frac{\alpha}{C_f^*}P = 0$$

The optimal level of each member's care and health is as follows:

$$\frac{C_f^*}{C_m^*} = \frac{\alpha}{\beta} \cdot \frac{w_m}{w_f}$$
$$H_m^* - H_f^* = (\alpha ln\alpha - \beta ln\beta) + (\alpha - \beta) \cdot lnP - \alpha lnw_f + \beta lnw_m$$

### Assumption 1: Gender wage gap

Assume that wage rate is different for male and female, and their production rate of providing care is the same. Namely we have $w_m > w_f$, $0< \beta = \alpha <1$. It yields:

$$\frac{C_f^*}{C_m^*} = \frac{w_m}{w_f} > 1$$
$$H_m^* - H_f^* = \alpha(lnw_m - lnw_f) > 0$$

Due to the gender wage gap, female member provides more care than male member, and female's health is worse than male's.

### Assumption 2: Intra-household labor division

Now we close the wage gap and assume females have absolute advantage of providing care. We have $w_m = w_f$, $0< \beta < \alpha <1$, and the optimal level of care and health is:

$$\frac{C_f^*}{C_m^*} = \frac{\alpha}{\beta} > 1$$
$$H_m^* - H_f^* = (\alpha ln\alpha - \beta ln\beta) + (\alpha - \beta)(lnP - lnw)$$

Female member ends up providing more care than her partner due to the intra-household labor division. The sign of health condition gap is ambiguous. Female member has worse health condition than male if $lnw - lnP < (\alpha ln\alpha - \beta ln\beta)/(\alpha - \beta)$.

With both Assumption 1 and 2, together with the intra-household labor division, the gender income gap further makes female allocate more time to providing care to her partner, and the gender health gap is larger than before.

$$\frac{C_f^*}{C_m^*} = \frac{\alpha}{\beta} \cdot \frac{w_m}{w_f} > \frac{\alpha}{\beta}$$

$$H_m^* - H_f^* = (\alpha ln\alpha - \beta ln\beta) + (\alpha - \beta) \cdot lnP - \alpha lnw_f + \beta lnw_m$$

$$> (\alpha ln\alpha - \beta ln\beta) + (\alpha - \beta)(lnP - lnw)$$

### Assumption 3: Infectious disease

So far, the only cost of providing care is the forgone income. Now consider a shock of infectious disease occurs in one family member. Providing care to the infected patient has a negative impact on the caregiver's health. Assuming the male is infected at the beginning, the new health production function is expressed as:

$$H_m = \bar{H}_0 + \alpha lnC_f - S$$

$$H_f = \bar{H}_0 + \beta lnC_m - \gamma lnC_f$$

where $S$ is an exogenous shock due to the initial infection of an infectious disease. $\gamma$ is the cost of providing care because the disease is infectious.[2] We assume $0 < \gamma < \alpha < 1$, otherwise no care will be provided to the infected member.[3] $C_m^{S*}$ and $C_m^*$ denote optimal care provided by male member with and without his getting infectious disease shock at the beginning, $C_f^{M*}$ and $C_f^*$ are optimal care provided by female member with and without her family member getting infectious disease shock at the beginning. The new optimal bundle of care and health is:

$$\frac{C_f^{M*}}{C_m^{S*}} = \frac{\alpha - \gamma}{\beta} \cdot \frac{w_m}{w_f}$$

$$H_m^{S*} - H_m^* = -S + \alpha lnC_f^{M*} - \alpha lnC_f^* = -S + \alpha[ln(\alpha - \gamma) - ln\alpha] < -S$$

$$H_f^{M*} - H_f^* = -\gamma lnC_f^{M*} = -\gamma ln\frac{(\alpha - \gamma)P}{w_f} < 0$$

This suggests that the male member's early infection makes the female provide less care than that in the infection-free condition due to the extra cost of caregiving. The second equation shows the negative effect on the male's health because infection is amplified to some degree due to the female's lower care provision, shown as $H_m^{S*} - H_m^* > -S$. Due to her partner's infection, female member ends up with a worse health condition, shown as $H_f^{M*} - H_f^* < 0$. This means

[2] If the initial health shock is a non-infectious disease, we assume the health production function is the same as that in disease-free case except a shock term $S$. In other words, providing care to family member with non-infectious disease is not costly and care provider's health condition is not affected by care providing time. There is potential depression or psychological effect of family member's infection of non-infectious disease or infectious disease, which could be represented as an additional level change in care provider's health: $H_f = \bar{H}_0 + \beta lnC_m - \gamma lnC_f - D$, where $D$ is the depression effect and is not affected by $C_f$, $\gamma$ equals one if member's initial health shock is infectious and zero otherwise. The existence of depression effect or not does not change the optimization over $C_m$ and $C_f$.

[3] We explore condition with $0 < \alpha \leq \gamma < 1$ in Appendix section S1.2.

infection makes the health condition of other member in the same household worse than that in the infection-free condition, namely a household penalty.

If the initial health shock takes place on the female member, the household penalty on male is:

$$H_m^{M*} - H_m^* = -\gamma ln C_f^{M*} = -\gamma ln \frac{(\beta - \gamma)P}{w_m}$$

Back to our question of interest, we are comparing the health condition of male and female under the condition of other member's infection. Under Assumption 1, household penalty is larger for female due to gender wage gap:

$$H_m^{M*} - H_m^* = -\gamma ln \frac{(\beta - \gamma)P}{w_m}$$
$$> H_f^{M*} - H_f^* = -\gamma ln \frac{(\alpha - \gamma)P}{w_f} = -\gamma ln \frac{(\beta - \gamma)P}{w_f}$$

Under Assumption 2, household penalty is larger for female due to absolute advantage of caregiving. In the following sections, we empirically quantify the household penalty for male and for female in the context of infectious disease.

$$H_m^{M*} - H_m^* = -\gamma ln \frac{(\beta - \gamma)P}{w_m}$$
$$> H_f^{M*} - H_f^* = -\gamma ln \frac{(\alpha - \gamma)P}{w_f} = -\gamma ln \frac{(\alpha - \gamma)P}{w_m}$$

# 4 Data

## 4.1 Insurance claims

We use de-identified health insurance claims from the COVID Research Database. It includes up-to-date claims and remittance data in all states across the US since 2016. We use diagnosis code to filter claims of infectious disease based on the CDC's ICD-10-CM code.[4] We are also able to observe patients' gender, year of birth, diagnosis date and healthcare providers' locations. Locations of patients are not available. The latest infection date in this study is August 1, 2020.

Besides, we use consumer data from AnalyticsIQ which creates a PeopleCore database using a blend of publicly available data and psychology-based algorithm. The database provides predicted characteristics of over 240 million individuals across 120 million households. Data fields cover people's demographics, finance, credit, housing, jobs, lifestyle, behaviors, etc[5]. We

[4] Available here: https://www.cdc.gov/nchs/icd/icd10cm.htm
[5] Details on AnalyticsIQ could be found here: https://analytics-iq.com/

obtain household-level variables from this database, including household identifiers, the number of children and adults, household income, and home value.

We use de-identified tokens to match individuals in these two datasets, and it gives us 1,125,908 individuals from 1,032,091 households in total. These individuals went to see a doctor at least once over the sample period whether for infectious or non-infectious diseases. Given the construction process, patients in this study tend to come from middle and higher-income groups with health insurance. Among all the merged patients, we restrict patients whose household includes at least one male and one female member. Eventually there are 80,478 individuals from 38,105 households in 50 states and 645 three-digit zipcode areas in our sample.

### 4.2 Survey data

To augment our analysis beyond administrative data, we employ a representative survey sourced from Mexico, namely the Mexican Labor Survey (ENOE). ENOE adopts a rotating panel design, conducting sequential household interviews spanning five quarters. An instrumental aspect of ENOE is its inclusivity, encompassing both the formal and informal labor sectors. This inclusivity is pivotal given the substantial prevalence of informal employment, a salient factor for our study, as our hypothesized mechanism may exert pronounced effects in the absence of formal health protection or insurance.

Our dataset spans the years 2005 to 2019, and our primary sample centers on two-person households, specifically those with both partners actively engaged in the labor force. We refine this by restricting our sample to individuals aged 15 to 50, yielding a dataset of approximately 17,000 couples per quarter.

The value of this dataset is multifaceted. It equips us to evaluate the impact of health shocks on labor market outcomes effectively. To identify a health shock, we consider an individual as “sick” if they were not working the previous week and attributed their absence to "illness, being excused, or personal affairs". However, contrary to insurance claims data, in the survey data we cannot distinguish who got sick first. We only observe whether a person was sick in the last week. Among the labor supply outcomes, we scrutinize are whether individuals were employed at all during the previous week and the number of hours worked.

Furthermore, this dataset provides occupation and family relationship details, enabling us to discern factors like the feasibility of remote work and household composition, including the presence of potential alternative caregivers. These variables facilitate the exploration of potential mechanisms underlying the results. Additionally, we have access to income data, enabling us to evaluate traditional models of labor supply within the family context.

# 5 Health Penalty using US Insurance Claims

Our empirical approach involves a consistent strategy across two complementary data sets, focusing on the arrival of health shocks. Initially, we examine the concept of "household penalty" in the context of health by utilizing insurance claims data from the United States. Next, we use the Mexican labor survey to shed light on the labor responses and the mechanisms behind the penalty.

## 5.1 Empirical strategy

To quantify the household penalty and its difference by gender in the insurance claims data, we use a standard difference-in-difference design:

$$\begin{aligned} Y_{ih} = \beta_0 + \beta_1 Member_i + \beta_2 Female_i + \beta_3 Female_i \times Member_i \\ + \beta_4 Age_i + \beta_5 Age_i^2 + \beta_6 HHSize_h + ZIP_h + \varepsilon_{ih} \end{aligned} \tag{1}$$

where the sample includes 80,478 patients with available claims, gender, and age. Their household information, including household identifier, income, and house sizes, is observed at each diagnosis. We exclude one-individual households from the sample. Table S1 shows household sizes, mostly ranging from 2 to 5, with an average of 4.5. Insurance claims span the period from 2016 to 2020. Within the 80,408 individuals, 7,806 have filed at least one infectious disease claim during the study period. $Member_i$ is an indicator that equals one if individual $i$ has an infected family member in the household that has been diagnosed with an infectious disease, captured by diagnosis code. $Member_i$ is interpreted as the treatment of household contagion exposure, whether $i$ is exposed to household infection or is only exposed to infection outside households. Consider two types of households in our sample, infected households and infection-free households. All individuals in infection-free households, as well as the very first infected members in infected households, are assigned $Member_i$ equal to zero, because the first patient is not exposed to other members' infection. They are considered the control group without household contagion. All individuals except the first patient in infected households are assigned $Member_i$ as one and they comprise the treated group.

Outcome $Y_i$ is an indicator that equals one if individual $i$ is infected by the same type of infectious disease as his/her family member's within one year, and infection timing is captured by diagnosis date. Within the treated group, those infected one year later than their members' or those never infected in an infected household have $Y_i$ equal to zero. Within the control group, all patient zeros are assigned $Y_i$ as one and those from infection-free households have $Y_i$ as zero. The control group is used to construct the baseline infection rate without household contagion exposure and its gender and geographic differences.

$Female_i$ is an indicator of being a female. Coefficient $\beta_2$ is the gender difference of infection rate due to biological vulnerability, protective behaviors or occupation difference and has nothing

to do with family transmission. Coefficient $\beta_1$ is the extra probability of getting infected due to an infected family member, the so-called household penalty. It captures the difference in the occurrence of infectious disease between the control and the treated group, namely between those facing only outside contagion and those facing both household contagion and outside contagion. The interaction term $Female_i \times Member_i$ captures the additional household penalty for females. The household penalty is estimated as $\beta_1$ for males and $\beta_1 + \beta_3$ for females.

Additionally, we add quadratic age terms, household size in a linear term or fixed effects, household income and home value on the right-hand side to control other characteristics that may affect the probability of infection. To control for unobservable geographic differences, we add three-digit zipcode fixed effects using the healthcare provider's location.

Our identifying assumption is that gender difference is the same for the treated and the control group if the household transmission channel is closed. In other words, the observed gender difference between these two groups solely comes from household contagion. Family member's infection may increase the awareness, and people may switch jobs to avoid interpersonal interactions or adopt more protective measures outside households, but this response is less likely to differ by gender. Besides, the insurance dataset may not be able to capture all the visits for infectious disease. We assume the latent probability is the same for the treated and the control group, namely the capability of capturing infectious disease visits in the claim data is the same for these two groups.

## 5.2 Main results

### 5.2.1 Summary statistics

Table S1 displays the number of patients by different household sizes in our sample. Household size ranges from 2 to 10, and the most common household structure is two adults and one child. Table S2 shows some summary statistics of the outcome and control variables. Individuals in our sample tend to be middle-aged with an average of 59 years old. We don't observe any kid infection. There are slightly more females than males, 50.6% of the total. The likelihood of a family member's earlier infection is 11.85%. Namely 11.85% of the individuals in our sample face household contagion and are considered the treated group, while the rest 88% only face contagion outside households. The control group includes all individuals in infection-free households and all the first infected member in infection households. The mean of the outcome variable is 9.7%. Outcome variable captures the occurrence of infectious disease anytime within our sample period for the control individuals, and the occurrence of infectious disease within one year of member's infection for the treated individuals. Thus, 9.7% is the weighted average of these two infection rates and is slightly smaller than the infection rate due to the restricted definition for the treated group. But it is similar to the simple infection rate since the control group is six times larger than the treated group.

In Table 1, the first three rows show the average outcome variable for all individuals, males

and females regardless of member's infection. Taking all individuals together, females are more likely to be infected than males, 10% vs. 8.5%, though the infection rates are not significantly different. Under the condition of no household contagion, the likelihood of being infected slightly goes down and its gender difference is similar to that of the unconditional mean. In contrast, the middle three rows show the probability of infection increases from 9.3% to 12.9% after a member's infection. Separating member's gender, females are much more likely to be infected when the early infection takes place in male member than that in female member, 14.4% vs. 12.9%. For males, their infection rates remain similar with and without male member's infection, 8.6% and 8.5%, but increase to 12.1% after female member's infection. The descriptive evidence shows there are significant male-to-female, female-to-female, and female-to-male transmission, but no obvious male-to-male transmission.

### 5.2.2 Household penalty and gender difference

Regression results from estimating equation (1) are reported in Table 2. Positive coefficients on $Member$ capture the impact of household contagion on other member's infection within one year. This confirms the higher likelihood of infection after a family member is infected. The coefficient remains similar after adding linear household size, household size fixed effects (9 dummies), household income, and house value on the right-hand side. The infection rate of individuals with infected member is higher by 1.2 percentage points compared with those without member's earlier infection. This household penalty is equivalent to 12.4% relative to the mean infection rate. Besides, the positive estimate of coefficients on $Female$ suggests females are more likely to be infected regardless of member's infection. This may be due to gender occupational difference and its associated exposure to contagion (Lewandowski et al., 2020) or different biological vulnerability. The coefficient of interest on the interaction term $Member \times Female$ is significant and positive. This indicates the household penalty is even higher for female members after controlling for the baseline gender infection difference. Due to household contagion, females are 2.2 percentage points more likely to be infected, 22.7% relative to the mean. The results are robust with and without household characteristics.[6]

To disentangle the effect of household size, in Table S3, we replace household size with the number of children and the number of adults in the household. Coefficients on $Member$, $Female$, $Member \times Female$, and $Age$ are quite similar to those in Table 2. Estimates on the new covariates show the probability of infection decreases with the number of adults in the household and is not significantly different for those living with a large or small number of children. This suggests that the close contacts among adult members contributes to the intra-household disease

[6]In terms of other covariates, the estimates on $Age$ and $Age^2$ show a nonlinear relationship between infection and age and the least vulnerable age is estimated to be 52 years old. Compared with the least vulnerable group, the infection rate of people who are 62 and 72 years old is 0.53 and 2.1 percent higher. Regarding household characteristics, the estimate on household size is negative but imprecise. When household income and home value are added in the regression, $R^2$ slightly increases from 0.353 to 0.357 and lower home value is associated with more infection. The results are consistent with previous findings that older people and the low income group are more seriously attacked by infectious diseases (Belot et al., 2020; Wiemers et al., 2020).

transmission.

Apart from infection within one year, we also use infection 1-2, 2-3, and 3-4 years after a member's infection to code the outcome variable. Results in Table S4 show imprecise estimates on $Member$ and $Member \times Female$ in all panels. There is a similar baseline gender infection difference as that in Table 2. The estimated household penalty is positive for 1-2 years' infection, but the estimate is not significantly different from zero and the magnitude is much smaller as the time gap increases. The positive estimates indicate the effect of member's infection on others infection 1-4 years later, and it could result from the spillover of member's effect within one year. Figure 1 displays the increased infection rate for the treated group for males and females, and the gender difference of increased infection. Similar to regression results, we only find household penalty within one year and no more penalty later. There is no gender gap in the increased infection rate after one year either. This suggests member's infection has no impact on other members' health outcomes after one year, neither does its gender difference.

#### 5.2.3 Within household comparison

We conduct a within-household comparison of gender difference only using individuals in the treated group with household contagion. We further require there is at least a male and a female member left after the first patient is dropped. Instead of a double-difference design, we conduct a single-difference analysis, drop $Member$ and the interaction term, and add household fixed effects. Other controls are the same as those in equation 1. Table S5 show a higher infection rate faced by females by 2.7 percentage points. The result shows a similar disproportionate household infection faced by females.

In the main specification without household fixed effects, we assume member's infection event does not change the baseline gender infection difference after closing household transmission channel. We explore the across-household within-zipcode variation and compare the gender difference in the treated and the control group. In this section, the within-household comparison shows female's disproportionate infection in comparison with her own male family member. The estimated gender difference is slightly larger. Though this practice results in a smaller sample size, larger standard errors and a restricted household structure with three or more members, we favor the within-household comparison to absorb any unobservable characteristics of households.

### 5.3 Heterogeneity results

In this section, we examine heterogeneous effects across family members' gender and age. We also explore heterogeneities by race and job in Appendix Section S2.

#### 5.3.1 Heterogeneous effects by member's gender

The observed household penalty comes from the impact of any family member's early infection regardless of member's gender. In this section, we separately use male and female member's

infection to code $Member$ and re-estimate equation (1). When analyzing the impact of male member's infection, the control group is exactly the same as before, i.e. individuals in infection-free households and all the household primary infections regardless of gender. For the treated group, we drop households with only female members' infection and only keep those exposed to male member's contagion.

Results in Table S6 show imprecise estimates on $Member_m$, which suggests the impact of other male member's early infection is not significant on male member. Namely there is no significant evidence of male-to-male transmission of infectious disease within households. The positive and significant estimates on $Member_m \times Female$ show the secondary attack rate of male-to-female transmission is 2.8 percentage points or 28.7% relative to the mean. An early infection on male member only affects female members in households. This is consistent with the conditional mean in Table 1 and is likely to result from female's caregiving to infected patients.

When using female member's infection to code $Member$, results in Table S7 show the same secondary attack rates for males and females. After females' infection, they may still need to do domestic work and provide care to other members, and the exposure to infection faced by other members is not significantly different by gender. Taking all family members together, the observed extra household penalty faced by females is driven by the significant male-to-female and insignificant male-to-male transmission. Besides, the likelihood of female-to-male infection is estimated to be 1.5 percentage points, smaller than that of male-to-female infection.

We also use the same sample as that in Table 2 and separate the first patient's gender to code $Member$. Namely we use two variables to replace $Member$ and add two interaction terms. Results in Table S8 show similar transmission patterns as those in Table S6 and S7. When the first infection in household is male, the increased infection rate for the other males and for females is 0 and 4.2 percentage points, respectively. Symmetrically, female's infection as the first patient in household increases males' and other females' infection rates by 3.3 percent.

### 5.3.2 Heterogeneous effects by member's age

Apart from member's gender, we also explore the heterogenous effects by the first patient's age. To do so, we separate individuals into three age groups and replace $Member$ with three dummies given the first patient's age. Results in Table S9 display the impacts of infected member with 40 and 60 years old as cutoffs.

Estimates on $Member_{old}$ and $Member_{old} \times Female$ show an infected member over 60 years old increases other male's and female's infection rate by 4.3 percentage points. There is no gender difference in secondary attack rates when the first patient is old. Similar patterns are found when the first infected is in his/her 20s and 30s. Both males and females face a higher infection rate by 3.5 percentage points, slightly lower than that from an old member's early infection.

In contrast, females face unequally higher infection risk when the first patient is 40-60 years

old. Potential explanation for this is that, the middle aged members are healthy in general. When they are infected, they need some care but not a lot. Not all the rest members are needed to care for them, and female member will take on this burden. In contrast, the old group may require intensive care provided by the rest members, and this results in higher exposure for both male and female. Another potential reason is that, the middle aged group contribute more to the household income. When they are infected, the loss of household income is high. The other members need to make up for the household income, and they don't want to lose one male worker with higher income. So only female is providing care to this middle-aged patient.

In Table S10, we further separate the outcome individual's age with the same cutoffs, 40 and 60, to separately check subgroup transmission patterns. Focussing on middle-to-young and old-to-middle transmission, the burden of taking care of older patients is unequally shared by females, captured by the positive estimates on $Member_{middle} \times Female$ in Column (1) and $Member_{old} \times Female$ in Column (2). In contrast the burden of taking care of younger patients is equally shared by males and females. The disproportionate household transmission faced by females in the pooled results is driven by females' taking care of older patients. Apart from the intergenerational transmission,[7] the within-age transmission is only significant in the old group, and old couples are likely to catch disease together. Among the six groups, young and middle-aged females below their 40s face the highest risk of getting infected.

### 5.4 Mechanisms

We find patterns consistent with the asymmetric household penalty being driven by household specialization. Specifically, given the two assumptions in Section 3, we test the heterogeneous patterns of household penalty by different gender income gap and different home production intensity.

First, the female penalty is larger in the areas with a higher gender income gap. We use income by gender data from the American Community Survey 2016 and calculate gender income gap for each zipcode area.[8] Then we separately estimate equation (1) for zipcode areas above and below the median and results are shown in Table S11. As is shown in Panel A, for individuals in areas with small gender income gap, the household penalty is still positive and large but estimates are imprecise. Moreover, the penalty is not significantly different by gender. The small and imprecise estimates on the interaction term suggest both males and females have a similar probability of infection with family member's early infection. In contrast, the positive estimates on $Member$ and $Member \times Female$ in Panel B show similar patterns as those in Table 2. Males have a 1.2 percentage points higher infection rate and females have a 2.4 percentage points higher rate. The

[7] In our sample, 26.2% of individuals live in intergenerational households where the gap between min and max age is over 20 years old.

[8] The geographic unit in the American Community Survey is the census block group. We use male and female's average income for each census block group, and calculate the population-weighted average male and female income for each zipcode area. Then we define gender income gap as male's income minus female's over male's, and separate zipcodes by the median gap.

observed results taking all areas together are mainly driven by areas with large gender income gap.

Second, the female penalty is larger in the areas where women spend more time on home production. On the second assumption, we use data from the American Time Use Survey to construct the gender difference of home production intensity at the zipcode level.[9] Table S12 displays estimation results using areas with smaller or larger gender gap. While females always face higher household penalty than males, in areas with higher gap of home production intensity, males are not affected by members' earlier infection. This indicates males in areas with relatively lower home production burden than females do not suffer from member's earlier infection. The gender gap of home production intensity drives the observed disproportionate household transmission and is likely to be the second mechanism.

### 5.5 Robustness

For robustness, we relax the requirement when constructing our sample. Instead of requiring at least a male and a female, we require two individuals in households regardless of their gender, and the new sample size is twice as large. In Table S15 Panel A, we find similar estimates on $Member$ and $Member \times Female$ to those in Table 2. Males and females are 1.5 percent and 2.5 percent more likely to be infected due to household contagion exposure.

Moreover, we use a subsample with no baseline gender infection difference and re-do the estimation, in case our results are driven by the higher probability of women seeing doctors than that of men. Results in Table S15 Panel B remain robust and the household penalty for males and females are estimated to be 2.2 and 3.2 percent, 22.4% and 32.5% relative to the mean.

As a placebo test, we use the infection of cancer (a non-infectious disease) to replace the outcome and $Member$. We find no effect of member's early infection on other member's infection and no gender difference, as is shown in Table S16.

## 6 Labor Penalty using Mexican Labor Survey

In addition to insurance claims, we complement our analysis with labor survey data from Mexico. This survey is representative of the Mexican population and offers robustness to potential selection inherent in insurance claims. We can also examine the household penalty's generalizability in a setting with a larger informal sector. Moreover, it allows us to address one of the important aspects of the model: the role of household income shares in shaping the household penalty.

These novel data not only affirm the presence of an asymmetric female health penalty but also unveil a labor penalty: women exhibit a more pronounced reduction in labor supply compared

[9] We use data after 2014 with precise county information and calculate the weighted average male and female's time allocated to home production. Then we calculate gender time gap as female's time minus male's over male's, and separate zipcodes by the median gap.

to men in response to their partners' illness. Moreover, our findings align with the model's predictions, showing that as the share of female income in the household increases, the female penalty diminishes, while the male penalty amplifies.

### 6.1 Empirical strategy

Our empirical strategy leverages partner's health shocks in the panel data to investigate the work-related outcomes within the working couples. We focus on two critical dependent variables: (1) whether an individual refrained from work in the previous week due to sickness or personal affairs (a binary outcome), and (2) the total number of working hours logged during the last week [10]. Our aim is to understand the interplay between gender, partner's sickness, and these outcomes.

$$\begin{aligned} Y_{ih} = \beta_0 + \beta_1 Member_i + \beta_2 Female_i + \beta_3 Female_i \times Member_i \\ + \gamma X_i + \varepsilon_{ih} \end{aligned} \tag{2}$$

The estimated parameter $\beta_1$ captures the effect of partner's sickness on work outcomes for men. It quantifies the change in expected work outcomes of males when their partners are sick compared to when they are not. The parameter $\beta_2$ measures the gender effect on work outcomes, independently of partner sickness.

Our central hypothesis pertains to $\beta_3$, the interaction term $Female_i \times Member_i$. This parameter quantifies the additional effect of partner's sickness on work outcomes for females compared to the effect for males. Importantly, it tests whether there is a gender asymmetry in the household penalty in labor outcomes. Additionally, we account for several control variables in our model. These include age and age squared, as well as fixed effects for quarter of the survey, state, municipality, and individual-level characteristics.

Next, we extend our analysis to understand the mechanisms driving the household penalty. We incorporate heterogeneity factors (represented by the HT term), which encompass variables related to the feasibility of working from home, the presence of an elderly woman in the household, and the share of female income. The extended regression equation is as follows:

$$\begin{aligned} Y_{ih} = \beta_0 + \beta_1 Member_i + \beta_2 Female_i + \beta_3 HT_i \\ + \beta_3 Female_i \times Member_i + \beta_4 Female_i \times HT_i + \beta_5 Member_i \times HT_i \\ + \beta_6 Female_i \times Member_i HT_i \\ + \gamma X_i + \varepsilon_{ih} \end{aligned} \tag{3}$$

[10] In case of not working last week, this variable has value of 0

These factors are relevant for working couples' dynamics and household composition. Our hypotheses are as follows: We anticipate that the feasibility of working from home may intensify the penalty faced by women when their partners are sick. The hypothesis is grounded in the idea that women, as primary caregivers historically, might be more inclined to opt for staying home to care for sick partners when remote work is possible.

The presence of an elderly female in the household is hypothesized to provide additional potential caregiving support. We expect households with an elderly female member to be better insulated from the negative consequences of partner's sickness, potentially reducing the impact on women's work outcomes.

Regarding the share of female income, we test whether household specialization determines the optimal care-giving level. A larger share of female income should lead to men being more likely to reduce working hours or take sick leave when their female partners are sick, reflecting comparative advantage within the household. Conversely, women, as primary income earners, are less likely to reduce their working hours or take sick leave when their male partners are ill, as it would disrupt the primary source of household income.

New parameters of interest shed additional light on the mechanisms of household penalty for women. $\beta_4$ quantifies how gender ($Female_i$) moderates the influence of the heterogeneity factor ($HT_i$) on work outcomes. It helps to discern whether the effect of variables like working from home feasibility, the presence of an elderly woman, or the share of female income differs between males and females within working couples. $\beta_5$ represents the interaction between partner's sickness ($Member_i$) and household dynamics ($HT_i$). It highlights how specific household characteristics modify the impact of partner's sickness on work outcomes of men. $\beta_6$ is the critical parameter of interest as it examines whether the heterogeneity term drives the gender asymmetry in the household penalty. Namely, it estimates how our heterogeneity terms mediate the additional impact of male's sickness on female's outcomes.

### 6.2 Main results

The results from estimating Equation (2), as presented in Table 3, provide substantial evidence of greater labor-related penalties for women. Specifically, in Panel A, we examine the likelihood of being 'Sick'. The analysis reveals a notable gender disparity: when the female partner in a working couple falls sick, there is a 3.8 percentage point increase in the probability of her male partner also being sick. In contrast, if the male partner is sick, the likelihood of the female partner being sick escalates by 11 percentage points. These differences are not only statistically significant but also economically meaningful, especially when considered in the context of the average probability of missing work in a given week, which stands at 1.5%.

"Hours Worked Last Week" outcome exhibits a similar gender asymmetry as presented in Panel B. In the main specification (Column (2)), we find that when female partner is sick, the male partner tends to work 3 hours less on average. These negative spillovers are again stronger

for females, providing additional evidence for household penalty. The interaction term indicates that when a male partner is sick, women reduce their labor supply by 4.6 hours, which is more than 10% of the mean hours worked during the week. Importantly, our results remain stable across specifications.

### 6.3 Heterogeneity results

In this section, we perform the heterogeneity analysis to explore the mechanisms driving the asymmetric gender penalty. We examine how it varies based on the ability to work from home, the presence of elderly females in the household, and income shares within the couple.

First, we find mixed results regarding the ability to work from home. In Panel A of Table S17, we do not find any evidence that work-from-home (WFH) arrangements impact the additional female penalty on the dummy of being sick. It does, however, affect the penalty in terms of hours worked. Panel B demonstrates that most of the effect on working hours is driven by women with jobs prone to work from home. In particular, after including the interaction with WFH, the asymmetric penalty only exists for women able to work from home. This suggests that staying at home to work might be linked to caregiving, hence a reduction in hours actually on the job. Interestingly, we see the opposite effect for men, indicating that they may not be subject to the same caregiving norm.

Second, the presence of an elderly female attenuates the female penalty for the working woman in the household. In Panel A of Table 4, the triple interaction term captures the change in female penalty for being sick when another elderly female is present in the household. Note that the sample differs in this regression as it also includes households with more than 2 members. The results tell us that the additional female penalty is 1.5 percentage points smaller when an elderly female is present, which is consistent with the insulating role of "grandmas". In Panel B, the coefficient on the triple interaction term is positive, indicating that the reduction in female working hours is smaller when an elderly female is present. However, this coefficient is not statistically significant.

Our analysis, emphasizing the female share of household income, strongly supports the theory of household specialization as a primary factor in the additional female penalty. As detailed in Panel A of Table 5, we focus on the interaction term representing the percentage of income contributed by women in a couple. The coefficient's magnitude indicates a significant shift: in households where the woman is the sole earner, the additional penalty associated with women falling ill is completely erased. Importantly, the income share does not influence the likelihood of men falling ill when their female partners are sick.

Panel B presents evidence supporting the household specialization, in terms of its influence on working hours. We find that when women are the main breadwinners, men tend to reduce their work hours more when their female partners face health problems. This trend holds true across different specifications. Moreover, when we account for individual differences, we observe

a positive and significant triple interaction effect. If a woman is the primary earner in the household, it helps offset the reduction in work hours that women typically experience when their partners have health issues. However, this result is not consistent across all specifications. Overall, these findings align with economic theories about how households allocate labor based on who can do the job most efficiently, and they suggest that households adapt their labor strategies based on their unique circumstances.

In conclusion, we find that the ability to work from home, the presence of an elderly caregiver, and the share of female income influence the spillover effects. In particular, the lack of ability to work from home, the presence of an elderly female, and the higher income share insulate women from the penalty.

# 7 Conclusion

This paper studies the spillover effects of health shocks on family members' health conditions and labor outcomes. Our empirical analysis covers both developed and developing countries, revealing the generalizability of household spillovers and the disproportionately adverse consequences faced by female household members.

We propose a concept, household penalty, and construct a theoretical framework on infectious disease transmission within households. One mechanism of gender inequality comes from the unequal distribution of household labor, with women consistently shouldering a heavier burden of housework and childcare responsibilities. In the context of infectious diseases, women's caregiving roles become even more pronounced, with their contributions taken for granted as they provide care to infected family members. Furthermore, the disproportionate infection rates among females may be a consequence of their additional housework burden due to other members' infections. With a smaller pool of household members available to perform housework, women are often left to shoulder a greater share of the remaining responsibilities, indirectly exacerbating their vulnerability.

Another potential mechanism lies in the income disparity between genders. If males within the household have higher incomes or serve as the primary breadwinners, the family may collectively decide to prioritize the protection of male members from infection or expedite their recovery if infected.

This paper bridges several fields of economics research, including the economics of household, health, labor, and gender economics. Our analysis underscores the importance of combining fields in future research. Besides, access to longer-term health records, especially those related to the COVID pandemic and seasonal influenza, will prove invaluable in expanding the sample size and deepening our understanding of the health crisis.

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Table 1: Unconditional and Conditional Infection Rate

| | Member's early infection | Infection mean | Std.Dev. | Observations |
|---|---|---|---|---|
| All | 0 or 1 | 0.0970 | 0.2959 | 80,478 |
| Male | 0 or 1 | 0.0887 | 0.2844 | 39,758 |
| Female | 0 or 1 | 0.1050 | 0.3066 | 40,720 |
| All | 0 | 0.0927 | 0.2899 | 70,944 |
| Male | 0 | 0.0847 | 0.2785 | 34,872 |
| Female | 0 | 0.1003 | 0.3004 | 36,072 |
| All | 1 | 0.1291 | 0.3353 | 9,534 |
| Male | 1 | 0.1175 | 0.3220 | 4,886 |
| Female | 1 | 0.1414 | 0.3484 | 4,648 |
| All | Male | 0.1368 | 0.3437 | 4,606 |
| Male | Male | 0.0864 | 0.2812 | 602 |
| Female | Male | 0.1444 | 0.3515 | 4,004 |
| All | Female | 0.1223 | 0.3277 | 5,625 |
| Male | Female | 0.1208 | 0.3259 | 4,594 |
| Female | Female | 0.1290 | 0.3354 | 1,031 |

*Notes:* There are 3909 individuals with only male member's early infection, 4928 only female's, 697 with both male and female's early infection

Table 2: Household Transmission of Infectious Disease

| | Infection dummy | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Member | 1.281** | 1.292** | 1.275** | 1.198* |
| | (0.631) | (0.631) | (0.630) | (0.638) |
| Female | 1.695*** | 1.691*** | 1.684*** | 1.679*** |
| | (0.270) | (0.271) | (0.271) | (0.272) |
| Member×Female | 1.049** | 1.055** | 1.043** | 1.032** |
| | (0.491) | (0.490) | (0.491) | (0.492) |
| Age | -0.536*** | -0.533*** | -0.516*** | -0.517*** |
| | (0.064) | (0.064) | (0.065) | (0.061) |
| $Age^2$ | 0.006*** | 0.006*** | 0.005*** | 0.005*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Household size | | -0.081 | | |
| | | (0.067) | | |
| Income | | | | -0.001 |
| | | | | (0.004) |
| Home value | | | | -0.003*** |
| | | | | (0.001) |
| $R^2$ | 0.0352 | 0.0352 | 0.0353 | 0.0357 |
| Observations | 80478 | 80478 | 80478 | 80478 |
| Y-mean | 9.697 | 9.697 | 9.697 | 9.697 |
| Zip FEs | Y | Y | Y | Y |
| Household size FEs | | | Y | Y |

*Notes:* Infection dummy is multiplied by 100. Robust standard errors are clustered at the zipcode level and reported in parentheses: * significant 10% level; ** significant at 5% level; *** significant at 1% level.

Table 3: Survey Results

| | (1) | (2) | (3) |
|---|---|---|---|
| **Panel A: Being sick dummy** | | | |
| Member | 0.042*** | 0.038*** | 0.039*** |
| | (0.002) | (0.002) | (0.003) |
| Female | 0.014*** | 0.014*** | |
| | (0.000) | (0.000) | |
| Member*Female | 0.074*** | 0.072*** | 0.070*** |
| | (0.004) | (0.004) | (0.005) |
| Age | -0.001*** | -0.001*** | -0.002 |
| | (0.000) | (0.000) | (0.002) |
| Age Squared | 0.000*** | 0.000*** | 0.000 |
| | (0.000) | (0.000) | (0.000) |
| Mean of Dependent Variable | 0.015 | 0.015 | 0.015 |
| Num.Obs. | 841632 | 839806 | 839806 |
| Std.Errors | by: Household | by: Household | by: Household |
| FE: Time | X | X | X |
| FE: State | X | X | X |
| FE: Municipality | | X | X |
| FE: Individual | | | X |
| **Panel B: Hours worked last week** | | | |
| Member | -3.251*** | -2.943*** | -2.430*** |
| | (0.220) | (0.219) | (0.228) |
| Female | -12.298*** | -12.305*** | |
| | (0.052) | (0.052) | |
| Member*Female | -1.850*** | -1.607*** | -1.628*** |
| | (0.394) | (0.392) | (0.399) |
| Age | -0.122*** | -0.178*** | 0.416+ |
| | (0.036) | (0.036) | (0.217) |
| Age Squared | 0.001 | 0.001** | -0.007* |
| | (0.001) | (0.001) | (0.003) |
| Mean of Dependent Variable | 39.688 | 39.700 | 39.700 |
| Num.Obs. | 841632 | 839806 | 839806 |
| Std.Errors | by: Household | by: Household | by: Household |
| FE: Time | X | X | X |
| FE: State | X | X | X |
| FE: Municipality | | X | X |
| FE: Individual | | | X |

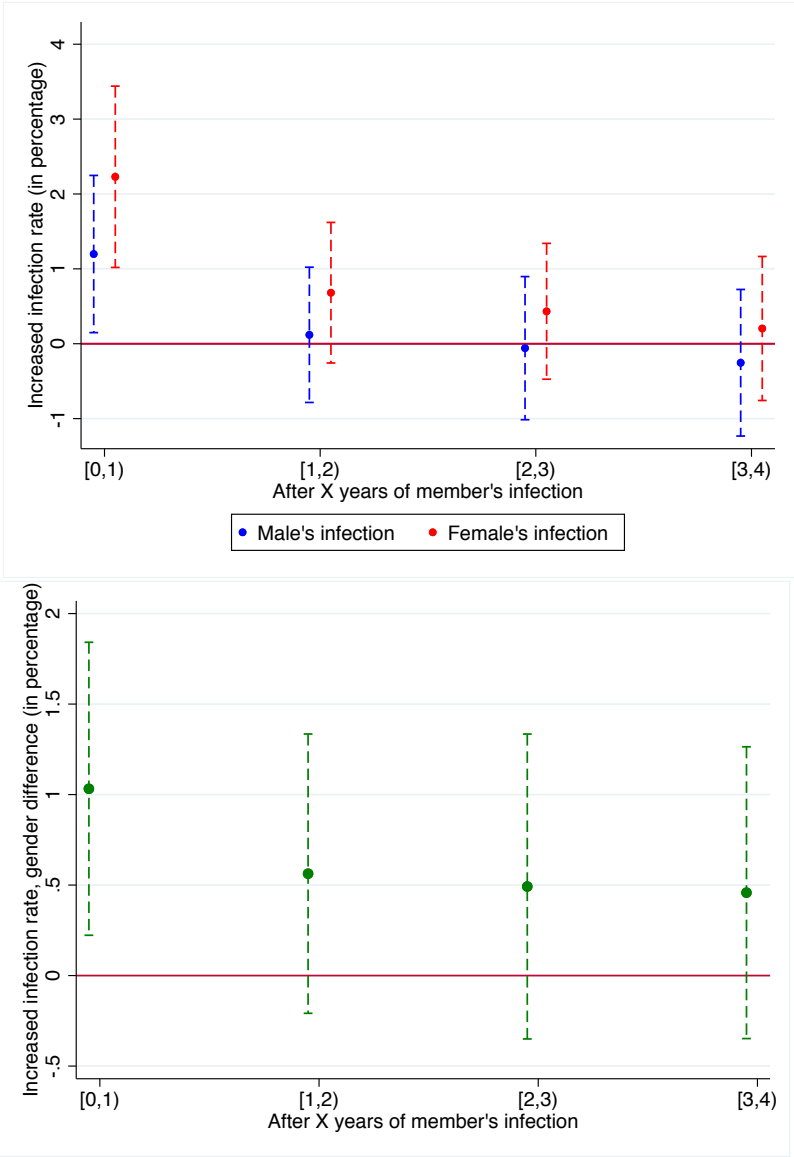
Table 4: Survey Results: Elder caregiver present

| | (1) | (2) | (3) |
|---|---|---|---|
| **Panel A: Being sick dummy** | | | |
| Member | 0.048*** | 0.047*** | 0.045*** |
| | (0.001) | (0.001) | (0.001) |
| Female | 0.006*** | 0.007*** | 3.141 |
| | (0.000) | (0.000) | (30.884) |
| Elderly Female | 0.001*** | 0.001*** | -1.640 |
| | (0.000) | (0.000) | (16.784) |
| Member*Female | 0.034*** | 0.033*** | 0.027*** |
| | (0.002) | (0.002) | (0.002) |
| Member*Elderly Female | 0.004 | 0.005 | 0.005 |
| | (0.004) | (0.004) | (0.004) |
| Female*Elderly Female | -0.004*** | -0.004*** | 0.547 |
| | (0.000) | (0.000) | (55.313) |
| Member*Female*Elderly Female | -0.014* | -0.014* | -0.012+ |
| | (0.006) | (0.006) | (0.006) |
| Mean of Dependent Variable | 0.012 | 0.011 | 0.011 |
| Num.Obs. | 7192930 | 7175003 | 7175003 |
| Std.Errors | by: Household | by: Household | by: Household |
| FE: Time | X | X | X |
| FE: State | X | X | X |
| FE: Municipality | | X | X |
| FE: Individual | | | X |
| **Panel B: Hours worked last week** | | | |
| Member | -3.371*** | -3.265*** | -3.010*** |
| | (0.116) | (0.115) | (0.111) |
| Female | -8.558*** | -8.760*** | 76.583 |
| | (0.022) | (0.022) | (21028.512) |
| Elderly Female | -1.772*** | -1.690*** | -46.079 |
| | (0.039) | (0.039) | (10212.801) |
| Member*Female | -0.199 | -0.054 | 0.089 |
| | (0.172) | (0.171) | (0.160) |
| Member*Elderly Female | 0.139 | 0.066 | -0.073 |
| | (0.334) | (0.332) | (0.324) |
| Female*Elderly Female | 3.390*** | 3.340*** | 27.538 |
| | (0.057) | (0.057) | (33324.347) |
| Member*Female*Elderly Female | 0.138 | 0.094 | 0.081 |
| | (0.473) | (0.469) | (0.455) |
| Mean of Dependent Variable | 41.406 | 41.417 | 41.417 |
| Num.Obs. | 7192930 | 7175003 | 7175003 |
| Std.Errors | by: Household | by: Household | by: Household |
| FE: Time | X | X | X |
| FE: State | X | X | X |
| FE: Municipality | | X | X |
| FE: Individual | | | X |

Table 5: Survey Results: Share of Female Income

| | (1) | (2) | (3) |
|---|---|---|---|
| **Panel A: Being sick dummy** | | | |
| Member | 0.025*** | 0.022*** | 0.019** |
| | (0.007) | (0.006) | (0.007) |
| Female | 0.016*** | 0.015*** | |
| | (0.001) | (0.001) | |
| Share fem. inc. | -0.020*** | -0.020*** | -0.023*** |
| | (0.001) | (0.001) | (0.001) |
| Member*Female | 0.157*** | 0.154*** | 0.152*** |
| | (0.017) | (0.016) | (0.018) |
| Member*Share fem. inc. | 0.007 | 0.005 | 0.011 |
| | (0.009) | (0.008) | (0.009) |
| Female*Share fem. inc. | -0.015*** | -0.014*** | -0.012*** |
| | (0.001) | (0.001) | (0.002) |
| Member*Female*Share fem. inc. | -0.176*** | -0.176*** | -0.176*** |
| | (0.025) | (0.024) | (0.028) |
| Mean of Dependent Variable | 0.014 | 0.014 | 0.014 |
| Num.Obs. | 768140 | 766598 | 766598 |
| Std.Errors | by: Household | by: Household | by: Household |
| FE: Time | X | X | X |
| FE: State | X | X | X |
| FE: Municipality | | X | X |
| FE: Individual | | | X |
| **Panel B: Hours worked last week** | | | |
| Member | -1.320* | -1.443* | -0.879 |
| | (0.646) | (0.639) | (0.638) |
| Female | -12.708*** | -12.752*** | |
| | (0.131) | (0.130) | |
| Share fem. inc. | 10.923*** | 10.872*** | 8.124*** |
| | (0.151) | (0.151) | (0.179) |
| Member*Female | -2.086* | -1.710+ | -4.102*** |
| | (1.029) | (1.021) | (1.068) |
| Member*Share fem. inc. | -2.903*** | -2.409** | -1.967* |
| | (0.859) | (0.850) | (0.896) |
| Female*Share fem. inc. | 5.341*** | 5.414*** | -0.635** |
| | (0.227) | (0.226) | (0.243) |
| Member*Female*Share fem. inc. | -1.757 | -1.832 | 4.172** |
| | (1.530) | (1.518) | (1.607) |
| Mean of Dependent Variable | 39.760 | 39.769 | 39.769 |
| Num.Obs. | 768140 | 766598 | 766598 |
| Std.Errors | by: Household | by: Household | by: Household |
| FE: Time | X | X | X |
| FE: State | X | X | X |
| FE: Municipality | | X | X |
| FE: Individual | | | X |

Figure 1: Increased infection rate for males and females (top) and its gender gap (bottom)



# Online Appendix

## S1 Additional Assumptions in Conceptual Frameworks

### S1.1 Family bargaining

In the main conceptual framework, we assume two family members are in total agreement, and they jointly conduct household consumption and jointly maximize their household utility. Now we assume members negotiate with each other to reach an agreement compromising different individual preferences. Based on Manser and Brown (1980) and McElroy and Horney (1981), we use the cooperative approach according to the Nash solution for further analysis. If they do not reach an agreement, they will instead choose their outside options. The Nash solution is characterized by cooperative gain sharing in order to maximize the product of the two individual gains:

$$max\ U_{C_m,C_f,x_m} = [U_m(x_m) - D_m]^b \cdot [U_f(x_f) - D_f]^{1-b}$$

where $x_m$, $x_f$ is male's and female's private consumption good. $D_m$, $D_f$ is male's and female's payoff when the partner does not agree, namely his or her outside option. The male member's bargaining power is an exogenous parameter $b$. $C_m$, $C_f$, budget constraint and health production functions are the same as those in the main model.

$$x_m + x_f \leq w_m(T - C_m) + w_f(T - C_f) + P(H_m - \bar{H}_0) + P(H_f - \bar{H}_0)$$

$$H_m = \bar{H}_0 + \alpha lnC_f$$

$$H_f = \bar{H}_0 + \beta lnC_m$$

The first-order conditions generate:

$$max\ \mathcal{L}_{C_m,C_f,x_m} = [U_m(x_m) - D_m]^b \cdot [U_f(x_f) - D_f]^{1-b}$$

$$+\lambda[w_m(T - C_m) + w_f(T - C_f) + P\alpha lnC_f + P\beta lnC_m - x_m - x_f]$$

$$\left.\frac{\partial \mathcal{L}}{\partial C_m}\right|_{C_m^*} = \lambda(-w_m + \frac{P\beta}{C_m^*}) = 0$$

$$\left.\frac{\partial \mathcal{L}}{\partial C_f}\right|_{C_f^*} = \lambda(-w_f + \frac{P\alpha}{C_f^*}) = 0$$

$$\frac{C_f^*}{C_m^*} = \frac{\alpha}{\beta} \cdot \frac{w_m}{w_f}$$

$$H_m^* - H_f^* = (\alpha ln\alpha - \beta ln\beta) + (\alpha - \beta) \cdot lnP - \alpha lnw_f + \beta lnw_m$$

The optimal level of each member's care and health condition is exactly the same as the main results without family bargaining. This results from the assumption that health is a pure investment good and does not enter the utility function, the only component affected by the bargaining assumption.

### S1.2 Too costly to provide care

Under the condition of male's initial infection of an infectious disease, now we assume $0 < \alpha \leq \gamma < 1$. The marginal cost of providing care (on the care provider's health) is higher than the marginal return of health (on the care receiver's health). In other words, transmission of the disease is very strong, so it's very risky to provide care to the infected member. Solving the first-order condition, household utility is decreasing with female's caregiving time, so she will provide the minimum level of care:

$$\frac{\partial x_c}{\partial C_f} = -w_f + \frac{P\alpha}{C_f} - \frac{P\gamma}{C_f} < 0$$

$$\frac{\partial x_c}{\partial C_m} = -w_m + \frac{P\beta}{C_m}$$

$$C_f^{M*} = 1 < C_f^* = \frac{P\alpha}{w_f}$$

$$C_m^{S*} = C_m^* = \frac{P\beta}{w_m}$$

$$H_f^{M*} = H_f^*$$

$$H_m^{S*} = \bar{H}_0 - S < H_m^* - S$$

There is no care allocated to the infected male member, and no household penalty for female. The male member is even worse than his condition under infection-free case by a level larger than $S$, the shock itself.

Under this extreme and brutal condition, family members will give up on the infected member and leave him/her aside. We should not see any family cluster of infectious diseases, which is contradicted with our observations. Household transmission aside, the strong infectious diseases must be controlled in a severe way like quarantine in a hospital because contact in everyday life is also risky. This is less likely to happen in the common infectious disease, so we focus on conditions with $0 < \gamma < \alpha < 1$ in the main conceptual framework.

# S2 Additional Heterogeneity Results

## S2.1 Heterogeneous effects by race composition

We test the heterogeneous effects using zipcode-level race composition. Table S13 shows how the proportion of the black group affects the household penalty. Areas with larger proportions of minority groups have lower household transmission rate, and its gender difference is not significantly different from that in areas with fewer minority group. This may result from the baseline worse health conditions of the minority group in the control group. If the minority group faces higher contagion outside households, it may absorb the observed household transmission effects.

## S2.2 Heterogeneous effects by jobs

Jobs are roughly classified in our sample, including real estate, sales, government, educator, etc. Given this constraint, we are not able to explore heterogeneity by jobs based on the level of inter-personal interactions or the capacity of working from home. In this section, we only test if being a healthcare worker affects the infection rate. To do so, we add an additional dummy variable to control for the individual being a healthcare worker. In Table S14 Panel A, the imprecise estimate on $Healthcare$ suggests no significant impact of being a healthcare worker on his/her own infection rate, though the sign is positive. The coefficients of interest remain stable with the additional control. Furthermore, we test if being a healthcare worker or if there is a healthcare worker in the household affects $\beta_1$ and $\beta_3$ using a triple-difference design. Results in Table S14 Panel B and C show it affects neither the household penalty nor its gender difference. This concludes that medical workers may face slightly higher risk of infection outside the household, but intra-household transmission pattern is not significantly different from that faced by people in other occupations.

## S3 Additional Tables

Table S1: Number of Patients by Household Size

| Household size | #Patients | #Children in household | #Patients | #Adults in household | #Patients |
|---|---|---|---|---|---|
| 2 | 12,629 | 0 | 20,069 | 1 | 735 |
| 3 | 14,220 | 1 | 36,828 | 2 | 26,894 |
| 4 | 16,356 | 2 | 10,646 | 3 | 23,622 |
| 5 | 14,742 | 3 | 7,571 | 4 | 16,660 |
| 6 | 10,749 | 4 | 5,364 | 5 | 8,006 |
| 7 | 6,598 | | | 6 | 4,561 |
| 8 | 3,185 | | | | |
| 9 | 1,488 | | | | |
| 10 | 511 | | | | |

Table S2: Summary Statistics

| | Observations | Mean | Std.Dev. | Min | Max |
|---|---|---|---|---|---|
| Infection | 80,478 | 0.0970 | 0.2959 | 0 | 1 |
| Member's early infection | 80,478 | 0.1185 | 0.3232 | 0 | 1 |
| Female | 80,478 | 0.5060 | 0.5000 | 0 | 1 |
| Age | 80,478 | 59.16 | 15.70 | 19 | 80 |
| Household size | 80,478 | 4.495 | 1.827 | 2 | 10 |
| #Children in household | 80,478 | 1.271 | 1.133 | 0 | 4 |
| #Adults in household | 80,478 | 3.224 | 1.198 | 1 | 6 |

Table S3: Household Transmission of Infectious Disease, Children and Adults in Household Added

| | Infection dummy | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Member | 1.296** | 1.272** | 1.195* |
| | (0.631) | (0.628) | (0.635) |
| Female | 1.696*** | 1.687*** | 1.682*** |
| | (0.271) | (0.272) | (0.273) |
| Member×Female | 1.066** | 1.057** | 1.044** |
| | (0.491) | (0.493) | (0.493) |
| Age | -0.548*** | -0.529*** | -0.527*** |
| | (0.064) | (0.064) | (0.061) |
| $Age^2$ | 0.006*** | 0.005*** | 0.005*** |
| | (0.001) | (0.001) | (0.001) |
| #Children | 0.090 | | |
| in household | (0.107) | | |
| #Adults | -0.223** | | |
| in household | (0.090) | | |
| Income | | | -0.000 |
| | | | (0.004) |
| Home value | | | -0.003*** |
| | | | (0.001) |
| $R^2$ | 0.0352 | 0.0355 | 0.0359 |
| Observations | 80478 | 80478 | 80478 |
| Y-mean | 9.697 | 9.697 | 9.697 |
| ZIP FEs | Y | Y | Y |
| #Children FEs | | Y | Y |
| #Adults FEs | | Y | Y |

*Notes:* Infection dummy is multiplied by 100. Robust standard errors are clustered at the zipcode level and reported in parentheses: * significant 10% level; ** significant at 5% level; *** significant at 1% level.

Table S4: Household Transmission of Infectious Disease, 1-4 Years

| | Panel A: Infection 1-2 years | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Member | 0.205 | 0.216 | 0.197 | 0.119 |
| | (0.544) | (0.545) | (0.543) | (0.549) |
| Female | 1.694*** | 1.690*** | 1.682*** | 1.676*** |
| | (0.270) | (0.270) | (0.271) | (0.272) |
| Member×Female | 0.579 | 0.585 | 0.573 | 0.563 |
| | (0.468) | (0.467) | (0.468) | (0.469) |
| Age | -0.542*** | -0.540*** | -0.522*** | -0.520*** |
| | (0.060) | (0.061) | (0.061) | (0.058) |
| $Age^2$ | 0.006*** | 0.006*** | 0.005*** | 0.005*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Household size | | -0.081 | | |
| | | (0.066) | | |
| Income | | | | -0.002 |
| | | | | (0.004) |
| Home value | | | | -0.002*** |
| | | | | (0.001) |
| $R^2$ | 0.0322 | 0.0322 | 0.0324 | 0.0328 |
| Observations | 80478 | 80478 | 80478 | 80478 |
| Y-mean | 9.532 | 9.532 | 9.532 | 9.532 |
| | Panel B: Infection 2-3 years | | | |
| Member | 0.026 | 0.038 | 0.019 | -0.059 |
| | (0.575) | (0.575) | (0.574) | (0.581) |
| Female | 1.691*** | 1.687*** | 1.679*** | 1.673*** |
| | (0.270) | (0.270) | (0.271) | (0.271) |
| Member×Female | 0.508 | 0.514 | 0.503 | 0.492 |
| | (0.512) | (0.512) | (0.512) | (0.512) |
| Age | -0.537*** | -0.535*** | -0.517*** | -0.516*** |
| | (0.061) | (0.062) | (0.062) | (0.058) |
| $Age^2$ | 0.006*** | 0.006*** | 0.005*** | 0.005*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Household size | | -0.083 | | |
| | | (0.066) | | |
| Income | | | | -0.001 |
| | | | | (0.004) |
| Home value | | | | -0.002*** |
| | | | | (0.001) |
| $R^2$ | 0.0318 | 0.0319 | 0.0320 | 0.0324 |
| Observations | 80478 | 80478 | 80478 | 80478 |
| Y-mean | 9.506 | 9.506 | 9.506 | 9.506 |
| | Panel C: Infection 3-4 years | | | |
| Member | -0.168 | -0.157 | -0.175 | -0.254 |
| | (0.589) | (0.590) | (0.588) | (0.595) |
| Female | 1.690*** | 1.686*** | 1.678*** | 1.673*** |
| | (0.270) | (0.270) | (0.270) | (0.271) |
| Member×Female | 0.474 | 0.480 | 0.468 | 0.458 |
| | (0.489) | (0.489) | (0.489) | (0.490) |

| | | | | |
|---|---|---|---|---|
| Age | -0.538*** | -0.535*** | -0.517*** | -0.516*** |
| | (0.060) | (0.061) | (0.062) | (0.058) |
| $Age^2$ | 0.006*** | 0.006*** | 0.005*** | 0.005*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Household size | | -0.083 | | |
| | | (0.065) | | |
| Income | | | | -0.002 |
| | | | | (0.004) |
| Home value | | | | -0.002*** |
| | | | | (0.001) |
| $R^2$ | 0.0316 | 0.0317 | 0.0318 | 0.0322 |
| Observations | 80478 | 80478 | 80478 | 80478 |
| Y-mean | 9.480 | 9.480 | 9.480 | 9.480 |
| ZIP FEs | Y | Y | Y | Y |
| Household size FEs | | | Y | Y |

*Notes:* Infection dummy is multiplied by 100. Robust standard errors are clustered at the zipcode level and reported in parentheses: * significant 10% level; ** significant at 5% level; *** significant at 1% level.

Table S5: Within Household Comparison

| | Infection dummy |
|---|---|
| Female | 2.745** |
| | (1.272) |
| Age | -0.8123** |
| | (0.3552) |
| $Age^2$ | 0.0085** |
| | (0.0034) |
| $R^2$ | 0.7928 |
| Observations | 3061 |
| Y-mean | 14.83 |
| Household FEs | Y |

*Notes:* Infection dummy is multiplied by 100. Robust standard errors are clustered at the household level, reported in parentheses: * significant 10% level; ** significant at 5% level; *** significant at 1% level.

Table S6: Household Transmission of Infectious Disease after Male's Infection

| | Infection dummy | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Member$_m$ | -0.340 | -0.251 | -0.292 | -0.461 |
| | (1.188) | (1.190) | (1.188) | (1.178) |
| Female | 1.656*** | 1.651*** | 1.636*** | 1.636*** |
| | (0.267) | (0.267) | (0.267) | (0.269) |
| Member$_m$×Female | 2.758** | 2.681* | 2.689* | 2.791* |
| | (1.373) | (1.376) | (1.373) | (1.366) |
| Age | -0.523*** | -0.520*** | -0.502*** | -0.499*** |
| | (0.066) | (0.067) | (0.067) | (0.063) |
| Age$^2$ | 0.005*** | 0.005*** | 0.005*** | 0.005*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Household size | | -0.093 | | |
| | | (0.068) | | |
| Income | | | | -0.002 |
| | | | | (0.004) |
| Home value | | | | -0.003*** |
| | | | | (0.001) |
| $R^2$ | 0.0348 | 0.0349 | 0.0350 | 0.0356 |
| Observations | 75550 | 75550 | 75550 | 75550 |
| Y-mean | 9.741 | 9.741 | 9.741 | 9.741 |
| ZIP FEs | Y | Y | Y | Y |
| Household size FEs | | | Y | Y |

*Notes:* The smaller sample size is because 4928 individuals with only female member's early infection are dropped. Infection dummy is multiplied by 100. Robust standard errors are clustered at the zipcode level and reported in parentheses: * significant 10% level; ** significant at 5% level; *** significant at 1% level.

Table S7: Household Transmission of Infectious Disease after Female's Infection

| | Infection dummy | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Member$_f$ | 1.585** | 1.592** | 1.574** | 1.503** |
| | (0.661) | (0.661) | (0.660) | (0.666) |
| Female | 1.703*** | 1.698*** | 1.690*** | 1.686*** |
| | (0.270) | (0.270) | (0.270) | (0.271) |
| Member$_f$×Female | 1.089 | 1.155 | 1.140 | 0.983 |
| | (1.283) | (1.278) | (1.283) | (1.293) |
| Age | -0.525*** | -0.522*** | -0.503*** | -0.504*** |
| | (0.067) | (0.068) | (0.069) | (0.066) |
| Age$^2$ | 0.005*** | 0.005*** | 0.005*** | 0.005*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Household size | | -0.084 | | |
| | | (0.068) | | |
| Income | | | | -0.000 |
| | | | | (0.004) |
| Home value | | | | -0.003*** |
| | | | | (0.001) |
| $R^2$ | 0.0330 | 0.0330 | 0.0332 | 0.0336 |
| Observations | 76569 | 76569 | 76569 | 76569 |
| Y-mean | 9.736 | 9.736 | 9.736 | 9.736 |
| ZIP FEs | Y | Y | Y | Y |
| Household size FEs | | | Y | Y |

*Notes:* The smaller sample size is because 3909 individuals with only male member's early infection are dropped. Infection dummy is multiplied by 100. Robust standard errors are clustered at the zipcode level and reported in parentheses: * significant 10% level; ** significant at 5% level; *** significant at 1% level.

Table S8: Household Transmission of Infectious Disease by the First Patient's Gender

| | Infection dummy | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Member$_m$ | -0.238 | -0.156 | -0.209 | -0.340 |
| | (1.290) | (1.288) | (1.286) | (1.279) |
| Member$_f$ | 3.051*** | 3.054** | 3.040** | 2.975** |
| | (0.659) | (0.658) | (0.656) | (0.662) |
| Female | 1.699*** | 1.694*** | 1.688*** | 1.683*** |
| | (0.271) | (0.271) | (0.272) | (0.273) |
| Member$_m$×Female | 4.198*** | 4.119** | 4.143*** | 4.235*** |
| | (1.600) | (1.601) | (1.601) | (1.596) |
| Member$_f$×Female | -0.369 | -0.297 | -0.306 | -0.454 |
| | (1.369) | (1.366) | (1.369) | (1.373) |
| Age | -0.530*** | -0.527*** | -0.510*** | -0.512*** |
| | (0.063) | (0.064) | (0.064) | (0.061) |
| Age$^2$ | 0.006*** | 0.005*** | 0.005*** | 0.005*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Household size | | -0.088 | | |
| | | (0.065) | | |
| Income | | | | -0.000 |
| | | | | (0.004) |
| Home value | | | | -0.003*** |
| | | | | (0.001) |
| $R^2$ | 0.0362 | 0.0362 | 0.0364 | 0.0368 |
| Observations | 80478 | 80478 | 80478 | 80478 |
| Y-mean | 9.697 | 9.697 | 9.697 | 9.697 |
| ZIP FEs | Y | Y | Y | Y |
| Household size FEs | | | Y | Y |

*Notes:* Infection dummy is multiplied by 100. Robust standard errors are clustered at the zipcode level and reported in parentheses: * significant 10% level; ** significant at 5% level; *** significant at 1% level.

Table S9: Household Transmission of Infectious Disease by the First Patient's Age

| | Infection dummy | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\text{Member}_{old}$ | 4.403*** | 4.406*** | 4.379*** | 4.323*** |
| | (0.799) | (0.799) | (0.797) | (0.801) |
| $\text{Member}_{middle}$ | 0.773 | 0.784 | 0.799 | 0.705 |
| | (0.936) | (0.935) | (0.934) | (0.947) |
| $\text{Member}_{young}$ | 3.591*** | 3.638*** | 3.596*** | 3.476*** |
| | (1.132) | (1.132) | (1.138) | (1.136) |
| Female | 1.688*** | 1.683*** | 1.677*** | 1.673*** |
| | (0.273) | (0.273) | (0.273) | (0.274) |
| $\text{Member}_{old}\times$Female | 0.888 | 0.894 | 0.877 | 0.883 |
| | (0.617) | (0.618) | (0.618) | (0.617) |
| $\text{Member}_{middle}\times$Female | 2.057** | 2.060** | 2.059** | 2.008** |
| | (1.011) | (1.011) | (1.013) | (1.015) |
| $\text{Member}_{young}\times$Female | -0.686 | -0.666 | -0.652 | -0.644 |
| | (1.589) | (1.586) | (1.588) | (1.588) |
| Age | -0.519*** | -0.516*** | -0.501*** | -0.504*** |
| | (0.062) | (0.063) | (0.064) | (0.060) |
| $\text{Age}^2$ | 0.005*** | 0.005*** | 0.005*** | 0.005*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Household size | | -0.089 | | |
| | | (0.066) | | |
| Income | | | | -0.000 |
| | | | | (0.004) |
| Home value | | | | -0.003*** |
| | | | | (0.001) |
| $R^2$ | 0.0367 | 0.0368 | 0.0369 | 0.0373 |
| Observations | 80478 | 80478 | 80478 | 80478 |
| Y-mean | 9.697 | 9.697 | 9.697 | 9.697 |
| ZIP FEs | Y | Y | Y | Y |
| Household size FEs | | | Y | Y |

*Notes:* Infection dummy is multiplied by 100. Robust standard errors are clustered at the zipcode level and reported in parentheses: * significant 10% level; ** significant at 5% level; *** significant at 1% level.

Table S10: Heterogenous Effects by Member's Age

| | Infection dummy | | |
|---|---|---|---|
| | Young | Middle | Old |
| | (1) | (2) | (3) |
| $\text{Member}_{old}$ | 0.962 | 0.611 | 4.994*** |
| | (2.314) | (1.414) | (0.898) |
| $\text{Member}_{middle}$ | -1.277 | -0.425 | 2.675 |
| | (1.833) | (1.051) | (1.661) |
| $\text{Member}_{young}$ | 0.823 | 4.863*** | 1.900 |
| | (2.025) | (1.806) | (2.196) |
| Female | 2.478*** | 1.760*** | 1.352*** |
| | (0.621) | (0.471) | (0.297) |
| $\text{Member}_{old}\times\text{Female}$ | 1.830 | 4.849*** | 0.588 |
| | (3.004) | (1.826) | (0.690) |
| $\text{Member}_{middle}\times\text{Female}$ | 10.885*** | 0.787 | -1.688 |
| | (2.697) | (0.944) | (2.180) |
| $\text{Member}_{young}\times\text{Female}$ | 1.082 | -2.159 | -3.947 |
| | (2.389) | (2.332) | (3.196) |
| Age | -0.912 | 0.493 | -2.211*** |
| | (0.725) | (0.555) | (0.515) |
| $\text{Age}^2$ | 0.014 | -0.005 | 0.018*** |
| | (0.012) | (0.005) | (0.004) |
| Income | 0.005 | -0.004 | 0.005 |
| | (0.011) | (0.005) | (0.006) |
| Home value | -0.005** | -0.003** | -0.003** |
| | (0.002) | (0.001) | (0.001) |
| $R^2$ | 0.0719 | 0.0447 | 0.0451 |
| Observations | 10302 | 29455 | 40721 |
| Y-mean | 9.913 | 8.299 | 10.61 |
| ZIP FEs | Y | Y | Y |
| Household size FEs | Y | Y | Y |

*Notes:* Infection dummy is multiplied by 100. Robust standard errors are clustered at the zipcode level and reported in parentheses: * significant 10% level; ** significant at 5% level; *** significant at 1% level.

Table S11: Heterogenous Effects by Zipcode-level Gender Income Gap

| | Infection dummy | | | |
|---|---|---|---|---|
| | Panel A: Areas where gender income gap is below the median | | | |
| | (1) | (2) | (3) | (4) |
| Member | 1.433 | 1.369 | 1.353 | 1.267 |
| | (1.183) | (1.188) | (1.193) | (1.197) |
| Female | 1.857*** | 1.870*** | 1.859*** | 1.858*** |
| | (0.456) | (0.457) | (0.458) | (0.455) |
| Member×Female | 0.024 | 0.007 | -0.037 | -0.014 |
| | (1.307) | (1.302) | (1.310) | (1.309) |
| Age | -0.769*** | -0.778*** | -0.754*** | -0.754*** |
| | (0.103) | (0.103) | (0.107) | (0.108) |
| $Age^2$ | 0.008*** | 0.008*** | 0.008*** | 0.008*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Household size | | 0.295** | | |
| | | (0.116) | | |
| Income | | | | -0.005 |
| | | | | (0.008) |
| Home value | | | | -0.002 |
| | | | | (0.002) |
| $R^2$ | 0.0505 | 0.0507 | 0.0511 | 0.0514 |
| Observations | 21127 | 21127 | 21127 | 21127 |
| Y-mean | 10.37 | 10.37 | 10.37 | 10.37 |
| | Panel B: Areas where gender income gap is above the median | | | |
| Member | 1.269* | 1.290* | 1.270* | 1.201* |
| | (0.652) | (0.651) | (0.653) | (0.655) |
| Female | 1.646*** | 1.635*** | 1.627*** | 1.622*** |
| | (0.339) | (0.339) | (0.339) | (0.339) |
| Member×Female | 1.244* | 1.260* | 1.257* | 1.235* |
| | (0.672) | (0.672) | (0.672) | (0.672) |
| Age | -0.454*** | -0.448*** | -0.434*** | -0.445*** |
| | (0.080) | (0.081) | (0.080) | (0.079) |
| $Age^2$ | 0.005*** | 0.005*** | 0.005*** | 0.005*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Household size | | -0.185*** | | |
| | | (0.068) | | |
| Income | | | | 0.003 |
| | | | | (0.005) |
| Home value | | | | -0.003*** |
| | | | | (0.001) |
| $R^2$ | 0.0280 | 0.0281 | 0.0282 | 0.0286 |
| Observations | 56392 | 56392 | 56392 | 56392 |
| Y-mean | 9.468 | 9.468 | 9.468 | 9.468 |
| ZIP FEs | Y | Y | Y | Y |
| Household size FEs | | | Y | Y |

*Notes:* Infection dummy is multiplied by 100. Robust standard errors are clustered at the zipcode level and reported in parentheses: * significant 10% level; ** significant at 5% level; *** significant at 1% level.

Table S12: Heterogenous Effects by Zipcode-level Time Use Difference

| | Infection dummy | | | |
|---|---|---|---|---|
| | Panel A: Areas where home production gap is below the median | | | |
| | (1) | (2) | (3) | (4) |
| Member | 2.632** | 2.633** | 2.613** | 2.514** |
| | (1.027) | (1.027) | (1.030) | (1.042) |
| Female | 1.418*** | 1.417*** | 1.414*** | 1.407*** |
| | (0.454) | (0.455) | (0.456) | (0.450) |
| Member×Female | 0.357 | 0.358 | 0.332 | 0.310 |
| | (0.848) | (0.848) | (0.848) | (0.851) |
| Age | -0.718*** | -0.717*** | -0.698*** | -0.689*** |
| | (0.121) | (0.121) | (0.119) | (0.120) |
| $Age^2$ | 0.007*** | 0.007*** | 0.007*** | 0.007*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Household size | | -0.011 | | |
| | | (0.093) | | |
| Income | | | | -0.003 |
| | | | | (0.006) |
| Home value | | | | -0.003 |
| | | | | (0.002) |
| $R^2$ | 0.0254 | 0.0254 | 0.0256 | 0.0264 |
| Observations | 27528 | 27528 | 27528 | 27528 |
| Y-mean | 9.405 | 9.405 | 9.405 | 9.405 |
| | Panel B: Areas where home production gap is above the median | | | |
| Member | 0.862 | 0.868 | 0.877 | 0.794 |
| | (1.055) | (1.053) | (1.055) | (1.052) |
| Female | 1.561*** | 1.555*** | 1.549*** | 1.539*** |
| | (0.550) | (0.548) | (0.549) | (0.551) |
| Member×Female | 2.233* | 2.238* | 2.213* | 2.213* |
| | (1.211) | (1.214) | (1.214) | (1.215) |
| Age | -0.526*** | -0.524*** | -0.506*** | -0.523*** |
| | (0.102) | (0.102) | (0.104) | (0.103) |
| $Age^2$ | 0.005*** | 0.005*** | 0.005*** | 0.005*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Household size | | -0.064 | | |
| | | (0.120) | | |
| Income | | | | 0.007 |
| | | | | (0.008) |
| Home value | | | | -0.005** |
| | | | | (0.002) |
| $R^2$ | 0.0415 | 0.0416 | 0.0418 | 0.0423 |
| Observations | 23141 | 23141 | 23141 | 23141 |
| Y-mean | 9.874 | 9.874 | 9.874 | 9.874 |
| ZIP FEs | Y | Y | Y | Y |
| Household size FEs | | | Y | Y |

*Notes:* Infection dummy is multiplied by 100. Robust standard errors are clustered at the zipcode level and reported in parentheses: * significant 10% level; ** significant at 5% level; *** significant at 1% level.

Table S13: Heterogenous Effects by Race Composition

| | Infection dummy | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Member | 2.438*** | 2.445*** | 2.430*** | 2.376*** |
| | (0.510) | (0.511) | (0.513) | (0.515) |
| Female | 1.725*** | 1.722*** | 1.716*** | 1.717*** |
| | (0.223) | (0.224) | (0.221) | (0.223) |
| Member×Female | 0.924** | 0.930** | 0.921* | 0.902* |
| | (0.458) | (0.456) | (0.462) | (0.463) |
| Black×Member | -0.137*** | -0.137*** | -0.138*** | -0.140*** |
| | (0.049) | (0.049) | (0.050) | (0.049) |
| Black×Female | -0.002 | -0.002 | -0.002 | -0.003 |
| | (0.018) | (0.017) | (0.017) | (0.018) |
| Black×Member×Female | -0.002 | -0.002 | -0.002 | -0.001 |
| | (0.057) | (0.057) | (0.058) | (0.058) |
| Age | -0.535*** | -0.533*** | -0.517*** | -0.522*** |
| | (0.055) | (0.054) | (0.059) | (0.057) |
| $Age^2$ | 0.006*** | 0.006*** | 0.005*** | 0.005*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Household size | | -0.058 | | |
| | | (0.036) | | |
| Income | | | | -0.001 |
| | | | | (0.002) |
| Home value | | | | -0.003*** |
| | | | | (0.001) |
| $R^2$ | 0.0347 | 0.0347 | 0.0348 | 0.0352 |
| Observations | 80478 | 80478 | 80478 | 80478 |
| Y-mean | 9.697 | 9.697 | 9.697 | 9.697 |
| ZIP FEs | Y | Y | Y | Y |
| Household size FEs | | | Y | Y |

*Notes:* Infection dummy is multiplied by 100. Black is in percentage and is absorbed by zipcode fixed effects. Robust standard errors are clustered at the zipcode level and reported in parentheses: * significant 10% level; ** significant at 5% level; *** significant at 1% level.

Table S14: Healthcare Workers

| | Infection dummy | | | |
|---|---|---|---|---|
| | Panel A: Additional control | | | |
| | (1) | (2) | (3) | (4) |
| Member | 1.281** | 1.292** | 1.275** | 1.196* |
| | (0.630) | (0.630) | (0.629) | (0.636) |
| Female | 1.689*** | 1.684*** | 1.675*** | 1.657*** |
| | (0.268) | (0.268) | (0.269) | (0.270) |
| Member×Female | 1.050** | 1.056** | 1.044** | 1.035** |
| | (0.491) | (0.491) | (0.492) | (0.492) |
| Healthcare | 0.098 | 0.115 | 0.144 | 0.397 |
| | (0.520) | (0.519) | (0.520) | (0.520) |
| Age | -0.537*** | -0.535*** | -0.518*** | -0.521*** |
| | (0.066) | (0.067) | (0.067) | (0.063) |
| $Age^2$ | 0.006*** | 0.006*** | 0.005*** | 0.005*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Household size | | -0.081 | | |
| | | (0.066) | | |
| Income | | | | -0.001 |
| | | | | (0.004) |
| Home value | | | | -0.003*** |
| | | | | (0.001) |
| $R^2$ | 0.0352 | 0.0352 | 0.0353 | 0.0358 |
| Observations | 80478 | 80478 | 80478 | 80478 |
| Y-mean | 9.697 | 9.697 | 9.697 | 9.697 |
| | Panel B: Triple difference | | | |
| Member | 1.287** | 1.298** | 1.281** | 1.203* |
| | (0.617) | (0.617) | (0.616) | (0.620) |
| Female | 1.658*** | 1.652*** | 1.644*** | 1.629*** |
| | (0.269) | (0.269) | (0.269) | (0.271) |
| Member×Female | 0.944* | 0.950* | 0.938* | 0.931* |
| | (0.507) | (0.507) | (0.508) | (0.509) |
| Healthcare | -0.998 | -0.987 | -0.947 | -0.583 |
| | (0.934) | (0.935) | (0.931) | (0.950) |
| Healthcare×Member | -0.155 | -0.152 | -0.167 | -0.242 |
| | (3.283) | (3.284) | (3.301) | (3.367) |
| Healthcare×Female | 1.237 | 1.243 | 1.231 | 1.097 |
| | (1.232) | (1.231) | (1.230) | (1.248) |
| Healthcare×Member×Female | 1.604 | 1.609 | 1.624 | 1.644 |
| | (3.370) | (3.373) | (3.393) | (3.446) |
| Age | -0.538*** | -0.535*** | -0.518*** | -0.522*** |
| | (0.066) | (0.067) | (0.067) | (0.063) |
| $Age^2$ | 0.006*** | 0.006*** | 0.005*** | 0.005*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Household size | | -0.082 | | |
| | | (0.066) | | |
| Income | | | | -0.001 |
| | | | | (0.004) |
| Home value | | | | -0.003*** |

| | | | | |
|---|---|---|---|---|
| | | | | (0.001) |
| $R^2$ | 0.0352 | 0.0352 | 0.0354 | 0.0358 |
| Observations | 80478 | 80478 | 80478 | 80478 |
| Y-mean | 9.697 | 9.697 | 9.697 | 9.697 |
| ZIP FEs | Y | Y | Y | Y |
| Household size FEs | | | Y | Y |

*Notes:* Infection dummy is multiplied by 100. Robust standard errors are clustered at the zipcode level and reported in parentheses: * significant 10% level; ** significant at 5% level; *** significant at 1% level.

Table S15: Results with Alternative Sample

| | Infection dummy | | | |
|---|---|---|---|---|
| | Panel A: Require two individuals in households | | | |
| | (1) | (2) | (3) | (4) |
| Member | 1.472** | 1.509** | 1.500** | 1.521** |
| | (0.639) | (0.636) | (0.636) | (0.639) |
| Female | 1.740*** | 1.746*** | 1.736*** | 1.683*** |
| | (0.193) | (0.193) | (0.193) | (0.197) |
| Member×Female | 0.949* | 0.947* | 0.941* | 0.986* |
| | (0.539) | (0.540) | (0.540) | (0.539) |
| Age | -0.399*** | -0.400*** | -0.391*** | -0.399*** |
| | (0.056) | (0.056) | (0.055) | (0.052) |
| $Age^2$ | 0.004*** | 0.004*** | 0.004*** | 0.004*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Household size | | -0.125*** | | |
| | | (0.043) | | |
| Income | | | | -0.004 |
| | | | | (0.004) |
| Home value | | | | -0.001 |
| | | | | (0.001) |
| $R^2$ | 0.0269 | 0.0270 | 0.0272 | 0.0274 |
| Observations | 167064 | 167064 | 167064 | 167064 |
| Y-mean | 9.602 | 9.602 | 9.602 | 9.602 |
| | Panel B: No baseline gender difference in infection rate | | | |
| Member | 3.260* | 3.341* | 3.326* | 3.294* |
| | (1.940) | (1.927) | (1.926) | (1.958) |
| Female | 0.335 | 0.318 | 0.312 | 0.314 |
| | (0.322) | (0.322) | (0.323) | (0.330) |
| Member×Female | 2.299** | 2.244* | 2.263** | 2.251* |
| | (1.151) | (1.145) | (1.146) | (1.143) |
| Age | -0.418*** | -0.409*** | -0.395*** | -0.412*** |
| | (0.106) | (0.107) | (0.104) | (0.107) |
| $Age^2$ | 0.005*** | 0.004*** | 0.004*** | 0.004*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Household size | | -0.347*** | | |
| | | (0.103) | | |
| Income | | | | -0.006 |
| | | | | (0.005) |
| Home value | | | | -0.003 |
| | | | | (0.002) |
| $R^2$ | 0.0583 | 0.0587 | 0.0589 | 0.0591 |
| Observations | 14437 | 14437 | 14437 | 14437 |
| Y-mean | 9.836 | 9.836 | 9.836 | 9.836 |
| ZIP FEs | Y | Y | Y | Y |
| Household size FEs | | | Y | Y |

*Notes:* Infection dummy is multiplied by 100. Robust standard errors are clustered at the zipcode level and reported in parentheses: * significant 10% level; ** significant at 5% level; *** significant at 1% level.

Table S16: Household Transmission of Cancer as a Placebo Test

| | Cancer infection dummy | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\text{Member}_{cancer}$ | -0.159 | -0.158 | -0.168 | -0.168 |
| | (0.269) | (0.269) | (0.269) | (0.269) |
| Female | 0.412*** | 0.411*** | 0.409*** | 0.409*** |
| | (0.040) | (0.040) | (0.040) | (0.041) |
| $\text{Member}_{cancer} \times$Female | -0.542 | -0.539 | -0.534 | -0.535 |
| | (0.376) | (0.376) | (0.372) | (0.373) |
| Age | 0.042*** | 0.043*** | 0.047*** | 0.047*** |
| | (0.014) | (0.014) | (0.015) | (0.014) |
| $\text{Age}^2$ | -0.000 | -0.000 | -0.000* | -0.000* |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Household size | | -0.029** | | |
| | | (0.014) | | |
| Income | | | | -0.000 |
| | | | | (0.001) |
| Home value | | | | 0.000 |
| | | | | (0.000) |
| Observations | 80478 | 80478 | 80478 | 80478 |
| R-square | 0.0141 | 0.0141 | 0.0142 | 0.0142 |
| Y-mean | 1.173 | 1.173 | 1.173 | 1.173 |
| ZIP FEs | Y | Y | Y | Y |
| Household size FEs | | | Y | Y |

*Notes:* Cancer infection dummy is multiplied by 100. Robust standard errors are clustered at the zipcode level and reported in parentheses: * significant 10% level; ** significant at 5% level; *** significant at 1% level.

Table S17: Survey Results: WFH

| | (1) | (2) | (3) |
|---|---|---|---|
| **Panel A: Being sick dummy** | | | |
| Member | 0.030*** | 0.028*** | 0.029*** |
| | (0.002) | (0.002) | (0.002) |
| Female | 0.007*** | 0.007*** | 0.874 |
| | (0.000) | (0.000) | (17.483) |
| WFH | -0.002*** | -0.002*** | 0.001 |
| | (0.000) | (0.000) | (0.001) |
| Member*Female | 0.045*** | 0.043*** | 0.047*** |
| | (0.004) | (0.004) | (0.005) |
| Member*WFH | -0.018*** | -0.017*** | -0.017*** |
| | (0.004) | (0.004) | (0.004) |
| Female*WFH | 0.006*** | 0.006*** | -0.001 |
| | (0.001) | (0.001) | (0.001) |
| Member*Female*WFH | -0.007 | -0.006 | -0.012 |
| | (0.012) | (0.012) | (0.012) |
| Mean of Dependent Variable | 0.009 | 0.009 | 0.009 |
| Num.Obs. | 813078 | 811369 | 811369 |
| Std.Errors | by: Household | by: Household | by: Household |
| FE: Time | X | X | X |
| FE: State | X | X | X |
| FE: Municipality | | X | X |
| FE: Individual | | | X |
| **Panel B: Hours worked last week** | | | |
| Member | -2.883*** | -2.604*** | -2.109*** |
| | (0.232) | (0.230) | (0.244) |
| Female | -12.351*** | -12.364*** | -35.425 |
| | (0.058) | (0.058) | (2589.941) |
| WFH | -7.392*** | -7.593*** | -0.299* |
| | (0.107) | (0.106) | (0.124) |
| Member*Female | -0.623 | -0.438 | -0.627 |
| | (0.456) | (0.453) | (0.475) |
| Member*WFH | 2.590*** | 2.308*** | 1.563** |
| | (0.571) | (0.567) | (0.543) |
| Female*WFH | 4.366*** | 4.415*** | 0.299+ |
| | (0.123) | (0.122) | (0.158) |
| Member*Female*WFH | -3.270** | -3.149** | -1.225 |
| | (1.054) | (1.043) | (1.000) |
| Mean of Dependent Variable | 40.458 | 40.467 | 40.467 |
| Num.Obs. | 813078 | 811369 | 811369 |
| Std.Errors | by: Household | by: Household | by: Household |
| FE: Time | X | X | X |
| FE: State | X | X | X |
| FE: Municipality | | X | X |
| FE: Individual | | | X |