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Labor Supply Responses to Health Shocks

Evidence from High-Frequency Labor Market Data from Urban Ghana

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Abstract

Workers in developing countries are subject to frequent health shocks. Using 10 weeks of high-frequency labor market data that were collected in urban Ghana, this paper documents that men are 9 percentage points more likely to work in weeks in which another worker in the household is unexpectedly ill. The paper provides suggestive evidence that these effects are strongest among very risk averse men, men in poorer households, and men who are the highest earners in their household. By contrast, women display a net zero response to another worker's illness, even women who are the highest earners in their household.

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1. Introduction

Health shocks are common in the developing world, and frequently severe enough to impair a worker's earning ability (Strauss and Thomas 1998). While formal sector contracts may insure workers against income loss due to health shocks (Gutierrez 2014), casual wage workers and the self-employed are not typically insured against such shocks. Furthermore, if the financial cost of treatment for injury or illness is high and few households have full insurance against these costs, then these income shocks occur at the same time that a typical household's marginal utility of income has increased. Given that many households are constrained in the ability to borrow and save, households may compensate for lost income due to an unanticipated injury or illness of a worker by increasing the labor supply of other members.

This paper documents such labor supply responses to illness shocks using high-frequency data on labor outcomes that we collected in urban Ghana during a 10 week period from August to October, 2013. High frequency data are crucial to interpret the effects of illness shocks, because credit constraints may prompt households to respond to an income shock at precisely the time it occurs. Our survey design also allows us to isolate unanticipated shocks (i.e., weeks in which the individual was planning to work but did not), minimizing the possibility that our estimate of the ex post response to a health shock is confounded by the household's ex ante risk mitigation behavior in response to anticipated shocks. We use individual and household-level fixed effects to control for possible correlation between the susceptibility to illness of an individual's household members and the unobserved determinants of his or her labor market outcomes. Moreover, short-lived illness spells tend to be under-reported in recall data, particularly among poor households (Das, Hammer, and Sánchez-Paramo 2012), but high-frequency data are plausibly less susceptible to such recall bias.

We begin by showing that unexpected health shocks are frequent. In particular, in any given week, 2.5 percent of men and 5.1 percent of women in the labor force at baseline missed the entire week to an unanticipated illness or injury (either their own, or to provide care for others' illness). In this environment, we find that labor supply is an important response to illness: male household members work more when another member misses work for a week due to an unexpected illness shock. In particular, men are 8.8 percentage points more likely to work at all, and they work 0.39 more days and 4.7 more hours, when a household member misses the entire week of work due to unexpected illness. This pattern of compensatory behavior is consistent across workers in a variety of job types (self and wage employment, work at home and away from home). By contrast, women do not change their average labor supply when another worker is unexpectedly ill, consistent with the need to provide caregiving as a countervailing force.

We then look for evidence of particularly strong responses among households (and specific members within households) whom economic theory predicts are particularly likely to work more in response to unanticipated income shocks. While examining heterogeneity is demanding of the data, and these results are accordingly not always statistically significant at conventional levels, we still argue that they provide broad suggestive evidence in line with theoretical models of labor supply in response to income shocks. In particular, poor households may be especially constrained in the ability to borrow and save (Jalan and Ravallion 1999; Dercon and Krishnan 2002; Sparrow et al 2014; Wagstaff and Lindelow 2014), and we correspondingly find suggestive evidence that the overall labor supply response is driven by males in households with less assets and education. We also find that compensation is driven by the most risk-averse men, who likely get particularly high disutility from income fluctuations.

Theory also predicts that the household members most likely to increase labor supply in response to an income shock are those with high gains (high salary), low opportunity cost of time at home while another household member is ill, or both. Indeed, men who are the highest earners in their households work 7.5 hours more in response to illness than men who are not. By contrast, even women who are the highest earners in their household do not work more in response to the illness of other workers, suggesting that their opportunity cost – presumably, the cost of caregiving – is even higher.

We then estimate the net effect of a worker's illness on household total labor supply and income, inclusive of this compensatory behavior. Despite the increases in labor supply from other males in the household, total household income and labor supply decrease when a household member is unexpectedly ill. Across all households, the effect of male and female illness is similar. However, when we turn to households with multiple male earners, the effect of a male illness is much more costly; income drops by 135 cedis (from an average of 241 cedis, or 101 US dollars at the 2013 exchange rate of 0.42 cedis to 1 dollar) when a man is ill, compared to a drop of 20 cedis when a woman is ill. By contrast, in households without male earners, female illness is particularly costly, leading to an income decrease of 115 cedis.

Health shocks thus appear costly enough for households to alter labor supply behavior in the context we study, despite the existence of the National Health Insurance program.[1] We thus build on the argument in Chetty and Looney (2006) that households in developing countries face greater welfare losses from shocks than those in developed countries because of the lack of social insurance; our results suggest that a national health insurance program still leaves households exposed to income shocks due to illness. Indeed, even after the expansion of the

[1] The program began in 2003 and was rolled out nationwide in 2005.

National Health Insurance Scheme, 11 percent of households in Ghana spent over 5 percent of their income on health in 2005 and 2006 (Akazili et al 2017).[2] Moreover, it is also likely that the illness of a worker represents a serious income shock -- even absent spending on health care -- in an environment where few workers have steady wage employment. Indeed, households appear to lack access to effective financial tools to smooth income shocks; for instance, only 47% of respondents at baseline reported having a bank account. These results are likely not unique to urban Ghana. Many developing countries have sizeable urban populations which are, by and large, less well insured against income shocks than their rural counterparts (Wagstaff 2007), face more frequent health shocks (Heltberg and Lund 2009), and frequently lack access to financial means to smooth income even when they live near banks (Banerjee and Duflo 2007).

Our results sit at the intersection of two literatures: household-level responses to health shocks in developing countries and labor supply responses to income shocks. Aside from the direct cost of treatment, negative health shocks also decrease household income by reducing workers' productivity (Pitt and Rosenzweig 1984; Thomas and Strauss 1997; Thomas et al 2006). Previous research has documented that households respond to health shocks by selling or consuming assets (Asfaw and von Braun 2004; Islam and Maitra 2012), borrowing (Islam and Maitra 2012; Mohanan 2013), or receiving transfers from other households (Asfaw and von Braun 2004; De Weerdt and Dercon 2006; Genoni 2012). The extent to which total consumption is smoothed varies by setting; Genoni (2012) and Mohanan (2013) cannot reject the null hypothesis of full consumption smoothing, while Dercon and Krishnan (2000), Gertler and Gruber (2002), Asfaw and von Braun (2004), and Sparrow et al (2014) find significant decreases

[2] This spending could come because an individual is not enrolled in the NHIS or is enrolled and does not have an insurance card (Akazili et al 2014), some conditions are not covered (Alhassan et al 2017), premia are charged, and user fees may be charged at health facilities (Akazili et al 2017).

in consumption after health shocks. While we do not have high-frequency consumption data that would be needed to provide a direct comparison to these results, we do provide evidence of a mechanism linking income fluctuations due to health shocks and household consumption at the time the shock occurs, and present evidence on patterns of heterogeneity that can help explain different levels of consumption smoothing across contexts. We also join Dercon and Krishnan (2000) -- who document that women's consumption particularly falls after health shocks -- in finding evidence that illness shocks have differential effects on specific household members.

Labor supply has not previously been emphasized as an important mechanism by which households in developing countries respond to income losses due to health shocks. Our results suggest that one explanation for previous null results is that the labor supply increase that we detect in urban Ghana using high-frequency data occurs contemporaneously with the health shock. By contrast, other papers use lower frequency data to examine the net effects that persist several months or years after a shock occurs. Indeed, Mohanan (2013) finds no net change in labor supply one year after households suffered a bus accident in India, and Gertler and Gruber (2002) find mixed evidence of labor supply responses of other household members when the household head experiences a reduction in his or her ability to conduct activities of daily living in a two-year interval between survey rounds in Indonesia. We argue that the concentration of effects around the time of the shock is a likely reason why we find clearer evidence of compensatory labor supply than the previous literature. Our findings also contrast with Aragon et al (2016), who find that in Peru, the labor supply of adults decreases in response to the pollution-induced illness of young or elderly household members, whose illness plausibly represents less of a shock to total household income than the illness of working-age members.

A second strand of related literature studies the tendency of households in developing countries to increase labor supply in response to income shocks.[3] Kochar (1999) finds that households increase their labor supply in response to idiosyncratic income shocks and Rose (2001) points out that households do so in response to aggregate shocks as well. Jayachandran (2006) further points out that households supply labor even when aggregate labor supply responses decrease the wage, suggesting that these households lack alternative ways to smooth risk. Building on these papers, we show that men in Ghana supply more labor even when a household member is ill, when the marginal value of domestic duties such as caregiving is high. While Kochar (1999), like us, finds labor supply responses only among male workers, our results suggest that gender differences in labor supply responses to shocks persist even in an environment with high female labor supply, suggesting a high value of caretaking. Correspondingly, Skoufias and Parker (2006) find that women in Mexico do work more when their husbands transfer into unemployment, and the value of caretaking is likely less salient.

This compensatory behavior also contributes to our understanding of urban labor markets in developing countries. While self-employment is often argued to offer greater flexibility than wage employment, we find that male workers whose primary jobs are in both wage and self-employment are able to increase their labor supply in response to other household members' illness. Moreover, even men who already report high regular hours of work (both relative to others in their household and in absolute terms) work more in response to the illness of other workers. Together, these results depict a dynamic urban labor force (Falco et al., 2011; Falco et al., 2014; Falco et al., 2015) in which men in a wide variety of employment situations are able to respond quickly to income shocks due to the illness of other workers in the household.

[3] While we focus on papers in developing country settings, compensatory labor supply behavior in response to negative income shocks has also been documented in the United States (Lundberg, 1985; Blundell, Pistaferri, and Saporta 2016), Italy (Baldini, Torricelli, and Brancati 2017) and Denmark (Fadlon and Nielsen 2015).

2. Data and Empirical Strategy

In this section we first describe the design of the high-frequency survey which allows us to identify the labor market impacts of unanticipated illness shocks, and then outline the characteristics of sample households and the empirical strategy we use to identify the labor market effects of these shocks.

2.1 Data Collection and Identification of Illness Shocks

The data come from a 10-week high-frequency data collection experiment we conducted in urban Ghana from August to October, 2013. The participants in this experiment were drawn from respondents of the Ghana Household Urban Panel Survey (GHUPS), who had previously been surveyed in 2010 and/or 2012.[4] This section summarizes the key aspects of the data collection that are relevant for estimating the effects of illness shocks on labor outcomes; more details on the overall data collection process are available in Heath et al (2019).

The survey encompassed 949 individuals in 365 households. The experiment was designed to examine how survey modality and the reference period affect the reporting of labor market outcomes. Participants were randomly assigned to one of three treatments – weekly surveys conducted by phone, weekly surveys conducted face to face, or tri-weekly surveys conducted by phone.

While Heath et al (2019) aggregate the triweekly data to weekly data to assess the role of survey modality and reference period on reporting of labor outcomes measured over comparable

[4] The GHUPS was run by the Centre for the Study of African Economies at the University of Oxford. See https://www.csae.ox.ac.uk/households/the-ghana-and-tanzania-urban-household-panel-surveys-2004-2006 for more detail on the original sample selection for the GHUPS.

time periods, in this paper, we primarily focus on the weekly sub-sample in order to identify severe illness shocks that lead to an entire week of missed work. Note also that the daily data we collected allow us to confirm that week-long illness shocks are more empirically relevant for labor supply than shorter illness shocks. Indeed, table A1 shows that there is no evidence of labor supply responses to another worker's absence from work in a given day. When we examine the time path of response to a daily illness shock using an event study framework in figure A1, we find some evidence of lagged responses among men, but these responses (a greater probability of working the day after illness, but a lower probability two days later) still lead to a net zero response during the period surrounding a daily illness shock.

Participants interviewed by phone were given a phone at the beginning of the survey to avoid the possibility of selection into the survey based on phone ownership. Respondents were paid 3 cedis ($1.36 US) for each completed phone survey. Together with the fact that surveys were quite short (4 minutes on average), 89 percent of scheduled weekly phone surveys and 94 percent of weekly in-person interviews were successfully conducted.

The illness shocks we can detect in this high-frequency data occur when a working-age adult did not work in a particular week, but had planned to work. These respondents were then asked to give the reason for missing work. In coding these free responses, we consider as an illness shock any response that mentioned the illness or injury of the respondent or another person. (See the online appendix for a list of the exact responses included as illness shocks.[5]) That is, we do not separately examine the effects of absence due to own illness and caretaking both for reasons of power and because we suspect that the modal response of "I was sick" – given in 74 percent of the instances of illness shocks that we categorize as illness – may reflect

[5] See http://faculty.washington.edu/rmheath/onlineappendix_HMR.pdf

both own illness and care, especially among men, who as indicated in table 1, never reported absence from work due to caretaking.[6]

Note that, as a result, the unanticipated shocks that we measure are a subset of the overall labor supply responses to illness. That is, if a respondent had planned ahead to stay home from work to help a relative who has been ill (or knew in advance they would not be able to work due to a chronic condition) they would not show up as having experienced a shock in our data because the absence was expected. We therefore cannot estimate the overall impact of illness on labor supply, since we do not observe instances in which a respondent was ill but worked or when an illness was so severe that it results in time periods when an individual was not even planning to work, which do not show up as unanticipated illness shocks in our data.

Ideally, we would have data on all health shocks, whether or not they disrupted planned labor supply, and we could compare labor supply responses to different kinds of illness shocks, broadly defined. But doing so would have required more survey time -- both because it would add another question asked to all respondents and because overall illness would be less well-defined and thus likely require more deliberation or clarification -- and we believe that the short survey length helped minimize attrition and maintain the quality of the responses. In any case, the unanticipated health shocks we can identify are interesting in their own right; they allow us to isolate ex-post compensatory behavior in response to unanticipated absences from work.

Figure 1 contextualizes the relative severity of the week-long illness shocks that are our key independent variable. Using reported labor supply in the previous day from the sample surveyed three times a week, it graphs the probability that a respondent is not working a given

[6] Panel A of table A2 tests for evidence of differential responses to other workers' absence due to caretaking versus other workers' absence due to their own illness. There is some evidence that among males, responses are strongest when another worker is absent due to caretaking.

number of continuous days after suffering an illness in day 1.[7] Conditional on missing a day of work due to unexpected illness, 28 percent of men and 44 percent of women are still not working 7 days later. A nontrivial fraction of the shocks continue even longer, especially for women: 31 percent of women are still not working 21 days after an unexpected illness, compared to 10 percent of men.

2.2 Summary Statistics

Table 1 presents summary statistics of the working-age adults in the high frequency sample.[8] The sample is relatively young (an average age of 34 for men and 36 for women) and well educated by developing country standards: the average male has 11.2 years of education and the average female has 9.4 years of education. The typical household extends beyond a nuclear family; the average male is in a household with 5.6 total working-age adults and the average female is in a household with 6.1 working age adults. In Heath et al (2019) we show that the sample closely matches the characteristics of adults in urban Ghana surveyed in the Ghana Living Standards Survey conducted in 2012 and 2013.

Both male and female labor supply is high in this context: 72 percent of men and 66 percent of women report being employed at baseline (having steady work that they were doing regularly), and 65 percent of men and 56 percent of women worked in a given week over the

[7] While these reports are suggestive of the typical length of an illness, these daily data are less suitable for precisely isolating illness shocks, given that we can identify illness only in days in which the individual was planning to work but did not. That is, a series of several consecutive days off would only appear if each day after the original illness shock, the individual was planning to go back to work but still could not. As a result, the rate at which respondents report seven consecutive days of illness shocks in the tri-weekly data (0.52% of weeks) is considerably lower than the rate at which they report a week of missed work due to illness in the weekly data (4.3% of weeks). This result further supports our primary focus in the empirical analysis on the respondents surveyed weekly.

[8] More than half (58%) of the respondents are female. This does not appear to reflect differential response rates by gender in the high-frequency survey, since a very similar percentage (57%) of adults in the household roster for the 2013 Labor Force survey from which the sample was drawn are female. The Ghana Statistical Service (2014) also reports that the 2010 Population and Housing Census found more females than males in Accra.

course of the high-frequency data collection. Conditional on working in a given week during the high frequency survey, women and men both work approximately the same number of total hours (47 hours for men and 45 hours for women). Self-employment is common, particularly among women: conditional on being employed at baseline, 70 percent of women and 48 percent of men are self-employed. Women employed at baseline earn less than men at baseline (reporting average usual weekly earnings of 95 cedis, compared to men's average of 162 cedis), and over the course of the high-frequency survey (reporting average earnings of 108 cedis to men's 163 cedis during weeks in which they worked).

Table 1 also indicates that health shocks that cause respondents to miss work on days/weeks in which they were planning to work are relatively common. Over the course of the survey, women who were in the labor force at baseline missed work due to an unexpected illness or caregiving duties in 5.1 percent of weeks; the figure for men was 2.5 percent of weeks. For men, all the reported days missed due to illness were for their own illness, whereas for women, 3.1 percent of weeks involved their own illness and 2.0 percent of weeks involved caregiving. Over the course of the survey, 14 percent of men and 21 percent of women employed at baseline missed at least one day of work due to unanticipated illness or caregiving.

2.3 Econometric Strategy: Individual-level responses to other workers' illness

We begin by examining individual level outcomes. For the labor supply outcome Y_{ijct} (namely, whether a respondent worked at all that week, and days and hours worked) for respondent i in household j in city c during week t, we estimate a fixed effects regression:

$$
\begin{aligned}
Y_{ijct} = \alpha_i + Female_{ijc} \times \lambda_t + \mu_c \times \lambda_t \qquad (1) \\
+ \beta_1 \times Other\ Worker\ Ill_{ijct} + \beta_2 \times Other\ Worker\ Ill_{ijct} \\
\times Female_{ijc} + \theta_1 \times Household\ Members\ Planning\ to\ Work_{jct} \\
+ \theta_2 \times Household\ Members\ Planning\ to\ Work_{jct} \\
\times Female_{ijc} + \varepsilon_{ijct}
\end{aligned}
$$

In addition to an individual-level fixed effect (α_i), we also include time fixed effects (λ_t), that are allowed to vary by gender ($Female_{ijc}$) and by city (μ_c)[9] to capture labor market fluctuations (which may differentially affect workers of one gender or within one city) within the ten weeks of the survey. The key independent variable ($Other\ Worker\ Ill_{ijct}$) equals one if another adult in the household missed the entire week of work due to unexpected illness (or caregiving) during a week in which she or he had planned to work. We allow the effect to vary based on the illness of the potential responder whose labor supply outcome we are examining; β_2 tests whether female workers display a differential response to the illness of another worker.[10] Note that, by construction, the individual did not work if he or she suffered an illness that we can measure, so we cannot examine the effects of a worker's illness on his or her own labor during the week in which it occurs. Because only those who are planning to work can report an illness, we condition on the number of household members planning to work in a given week ($Household\ Members\ Planning\ to\ Work_{jct}$), and allow its impact to vary by gender. We

[9] An exception is a few specifications (in particular, figure 2 and tables A3, A6, A7 (panel A) and A8), in which the objective function of the tobit estimation behaves poorly when these fixed effects are included.
[10] This specification raises the question of whether the individual-level response to a worker's illness varies based on the sex of the ill worker (in addition to the sex of the worker responding, as tested by β_2). Panel B of table A2 examines this question by including the additional regressors *Other Worker Ill$_{ijt}$ X That Worker is Female$_{jt}$ and Female$_i$ X Other Worker Ill$_{ijt}$ X That Worker is Female$_{ijt}$*. We do not find strong evidence that the response of either male or female workers varies based on the gender of the worker who is ill.

focus on the sample of workers employed at baseline (68 percent of the sample).[11]

The individual fixed effect captures time-invariant factors that affect both labor market outcomes and illness shocks of household members, such as the individual's health endowment, which could be correlated with the endowment of other household members. It also accounts for household-level factors such as the household's permanent income or the availability of other caregivers nearby. Then the estimated β_1 and sum of β_1 and β_2 provide the causal effect of a health shock to another worker in the household on male and female respondents, respectively, if there are no time-varying variables that affect both illness and labor supply (conditional on the sample-wide shocks reflected in the time fixed effects). That is, the identifying assumption is that $E\left(Other\ Worker\ Ill_{ijct}\ \varepsilon_{ijct}\right) = 0$. An omitted variable (such as a negative shock to unearned income that would both increase labor supply and reduce a household's ability to invest in preventative health inputs) would need to affect both health and labor supply in the same week in order to create an endogeneity concern.

While it seems unlikely that actual illness is endogenous to time-varying determinants of labor supply, two remaining concerns could violate the identification assumption. First, even if illness occurs at random, absence from work due to illness could be endogenous to productivity shocks at work. That is, it may be less costly to take off work during low productivity times. If this pattern is occurring, it will affect our estimates of the compensatory behavior of other household members if there are correlated productivity shocks between household members. We partially address this concern by means of the control for the number of family members planning to work each week (interacted with gender). This control deals with shocks that have

[11] Table A3 re-estimates equation 1 on the sample of adults who were not employed at baseline and confirms that respondents who are not employed at baseline do not appear to increase their labor supply in response to the illnesses of other laborers in the household, suggesting that short term illness shocks do not seem to induce individuals without regular employment to work more.

already occurred when family members are planning their labor supply for the week, leaving as a remaining concern shocks that occur after labor supply is planned.

If such shocks occur, we would be particularly concerned about a negative correlation, which would mean that one member has low productivity (and is more likely to take off work due to illness), when another member has high productivity (and thus works more), and thereby generate a pattern of effects that looks like the compensatory labor supply response we detect among men. While ex-ante risk sharing in occupational choice would predict such a pattern of correlation in productivity shocks, we conduct two tests that provide reassurance that it is unlikely to be the main driver of our estimations of compensatory behavior. First, in table A2 (panel C), we test whether the compensatory response differs based upon whether the ill worker is wage or self-employed, under the premise that absence from wage employment due to illness is less likely to be driven by productivity shocks (given that the marginal return to working more hours is plausibly less closely tied to short-term productivity shocks). The responses to the sickness of self-employed and wage workers are indeed very similar. Second, we test for the presence of correlated labor shocks in the sample of households who never reported an illness in the survey by substituting the regressor $Other\ Household\ Members\ Working_{ijct}$ for the regressor $Other\ Worker\ Ill_{ijct}$ in equation (1). This estimation, given in table A4, results in a close-to-zero and statistically insignificant correlation between the number of family members who worked and a male's labor supply, conditional on the number of family members planning to work. By contrast, for each family member who works during a given week, a woman works 0.34 more days and 4.3 more hours. This pattern suggests that there is if anything a positive correlation in labor supply shocks among female household members, which suggests that absent such shocks we may have also seen a positive labor supply response among females, as well as males.

A second potential violation of the identification assumption would occur if a localized aggregate illness shock affects labor demand. That is, if many workers in a particular area have an illness (say, the flu) all at once and are absent from work, this labor supply shock could shift up wages/earnings, inducing increased labor supply among other workers in the same labor market. This story is also consistent with the lagged labor supply response to illness we will discuss in section 3.1. The inclusion of city X week fixed effects controls for such shocks, if the relevant area experiencing the labor demand shock is the city. While many contagious illnesses are likely city-wide, we acknowledge that it is possible that some shocks may operate at a finer level. The finest level of geography we have in our data is the enumeration area of which we have 59 in the data, so including enumeration area X week fixed effects takes up a lot of degrees of freedom in the estimation. Accordingly, the standard errors in the fixed effects regression for labor supply on the extensive margin increase, and we can no longer estimate the fixed effects tobit specification for hours and days. Nonetheless, our main results are broadly consistent with this specification, and we believe the fact that the main results come through even in a specification which is demanding of the data as reassurance that our main result is robust. See table A5 for individual results and online appendix table O4 for household-level results.

Finally, aside from the specific arguments we have made against each type of shock that could violate the exclusion restriction, we also highlight that the pattern of heterogeneity of effects on men – effects driven by men in poor households, who are risk averse, and who are high earners within their households – fits theoretical models of household labor supply, but is not obviously predicted by a pattern of correlated productivity shocks in households that faced illness during the survey.

A related consideration is whether illness shocks affect the probability that a survey is successfully completed. Heath et al (2019) point out that attrition is very low and difficult to predict on the basis of observable worker and household characteristics: 91% of the weekly interviews scheduled were successfully conducted. Missed surveys very rarely correspond to complete disappearance from the survey; only two of the 949 respondents in the high frequency data were not available at endline. Moreover, note that even if missed surveys do correlate with illness in the household, this would only bias the estimated effect of illness on labor supply if this pattern differentially holds among respondents who were more or less likely to work during a given illness episode suffered by another family member. Finally, since missed surveys affect the probability that we can detect an illness – we only know an individual was ill if he or she responds to the survey – our control for the number of household member planning to work in a round also accounts for the fact that we have a greater chance of detecting sickness in rounds in which more household members were surveyed.

2.4 Econometric Strategy: Net effects of illness on households

To estimate the net effect of a household member's illness on the household, inclusive of the compensatory behavior of other workers, we also examine the effect of a household-level illness shock ($Worker\ Ill_{jt}$) – a worker missing a week of work due to unexpected illness in a given week – on household-level outcomes (Y_{jt}), namely, total labor supply and earnings. We include household (γ_j) fixed effects and time fixed effects interacted with city ($\lambda_t \times \mu_c$):

$$
\begin{aligned}
Y_{jct} = \gamma_j + \lambda_t \times \mu_c & \\
& + \delta_1 \times Worker\ Ill_{jct} + \delta_2 \times Worker\ Ill_{jct} \times Female\ Ill_{jct} \\
& + \theta_1 \times Household\ Members\ Planning\ to\ Work_{jct} \\
& + \theta_2 \times Household\ Members\ Planning\ to\ Work_{jct} + \varepsilon_{jct}
\end{aligned} \tag{2}
$$

The estimated δ_1 then indicates the net effect of an illness shock to a male worker after the household has undertaken compensatory behavior. We allow this effect to vary based on whether the worker who is absent from work because of an illness shock is female, so that the sum of δ_1 and δ_2 provides the overall effect of the illness of a female worker on the household. Analogously to the identification assumption in the individual-level regression, δ_1 and the sum of δ_1 and δ_2 represents the causal effect of the unexpected illness of a male and female household member, respectively, if there are no time-varying variables that affect both the probability of illness of a worker and overall household labor supply: $E\left(Worker\ Ill_{jct}\ \varepsilon_{jct}\right) = 0$. This assumption again seems plausible, given that most time-varying determinants of labor outcomes and health are either fixed over the course of a short survey or if they change, are still unlikely to affect the labor outcomes and health of workers in a household during precisely the same week.

While we examine household-level earnings, given its key role in overall welfare,[12] we highlight the caveat that, to keep the survey as short as possible, we did not ask earnings directly for wage workers. Instead, we asked about hours worked, and calculate earnings under the

[12] While we do not focus on individual-level income results, table A6 confirms that the same broad patterns that are present in individual-level labor supply results hold for individual level income results as well.

assumption that respondents earn their usual baseline pay for each hour worked unless they indicated a change in the payment terms under which they were employed; see appendix A for details.

3. Results

We begin by describing the individual level regressions that estimate workers' responses to the illness of other workers in the household, first providing overall effects and then testing for differential responses among workers in households that economic theory predicts would be particularly likely to increase their labor supply in response to the illness shocks of other workers. We then provide evidence of the plausibility of the main mechanism that we believe is generating our results – that workers work more in order to increase their take-home pay and compensate for the lost income due the absence from work of another household member. We conclude by estimating the net effect of a worker's illness on household level outcomes.

3.1 Individual-level outcomes

Table 2 shows a worker's response to the illness of another worker during a given week. We begin by displaying overall effects, across both genders of potential responders, which are close to zero and not statistically significant. Panel B indicates that these average effects mask considerable heterogeneity by gender. This heterogeneity is to be expected if households divide labor according to comparative advantage, and women have a comparative advantage in caretaking over men. The first column indicates that a male worker is 8.8 percentage points more likely to work in a week in which another household member was unexpectedly ill. This effect is large, relative to the overall probability of 0.85 (as displayed in table 1) that a man who was employed at baseline worked in a given week over the course of the survey. They also work an average of 0.394 more days (P = 0.13) and 4.7 more hours as a result of the illness of a fellow worker in their household.

By contrast, women's labor supply responses are on average close to zero on both the extensive and overall margins. This estimated net zero on women does not rule out countervailing effects that mask compensatory labor supply in a subsample of women. In particular, since the estimates are unconditional on the respondent's own reports of missing work due to her own illness or caregiving, some women could work more when a household member is ill, while others work less in order to care for that household member or take over other duties around the house. Indeed, table 1 indicates that women are the only ones who report missing work due to caregiving in this sample.[13]

However, since table A4 documented a positive correlation in labor shocks among female household members that could also lower the estimated compensatory behavior of females, we also look for direct evidence of caretaking, and find suggestive evidence, which is displayed in table A7. First, while we argued in section 2.1 that we are concerned that our data do not provide a sharp distinction between missed work due to own illness and caretaking, we can nonetheless construct a binary variable that equals 1 if the household member missed work, and the reported reason was caretaking. Recall that only women report caretaking, so in a regression of only women, we estimate whether missed work due to caretaking is more likely during weeks in another worker in the household is unexpectedly ill. While panel A of table A7 finds a large

[13] While the indication that men experienced precisely zero instances of missed work due to caretaking may be influenced by measurement error – for instance, if social norms against male caregiving made men hesitant to report caregiving or prompted enumerators to code some instances of caregiving as men's own illness – it nonetheless is likely that caretaking is considerably more prevalent among women.

point estimate relative to the mean rate of missed work due to caregiving (2.0 percent of the weeks among women employed at baseline) – a woman is 0.8 percentage points more likely to report caretaking in a week when a fellow worker is unexpectedly ill – this effect is noisily estimated and thus not statistically significant. Given this suggestive but inconclusive result, panel B of table A7 conducts an additional test that assesses whether women with greater care-taking duties – as proxied by whether they engage in any child care over the course of the survey (we did not ask about care of sick adults) – have differentially negative labor supply response to the illness of other workers. Fifty-eight percent of men and 78 percent of women engaged in child care at some point in the survey. Indeed, women who engage in child care are 7.9 percentage points less likely than women who do not engage in child care to work during a week in which another worker in the household is unexpectedly ill; they also work 0.55 fewer days and 3.7 fewer hours. However, as in panel A, none of these results is statistically significant, so we view table A7 as broadly providing suggestive evidence in line with the possibility that the net zero average effect on women conceals a negative effect on women who are likely caregivers.[14]

While our main specification focuses on the contemporaneous effect of the illness of a family member, we can take advantage of the temporal dimension of our data to test for anticipation effects or persistent responses. In particular, we include a lag and lead of the independent variable in an event study framework, and we also test whether a lead and lag of the worker's own shock ($Self\ Ill_{ijct+1}$ and $Self\ Ill_{ijct-1}$) are significant, conditional on the independent variable ($Other\ Worker\ Ill_{ijct}$). In the event study, we only include one lead and lag because, with only ten weeks of data, including more leads and lags compels us to drop

[14] Interestingly, men who are child-caregivers are more likely to respond to the illness of other households, perhaps because of a greater sense of obligation to the household.

almost half (or more) of our data points.[15]

A caveat in interpreting these results, however, is that we cannot be confident that onset of illness coincides perfectly with the start of the reporting period. For instance, if one family member misses work for an entire reporting period – and then the first few days of the next reporting period (but not the whole week) – and another household member compensates for the duration of the illness, this behavior would look like a both a contemporaneous and a lagged response. Similarly, if a family member misses the last part of a reporting period and then the next week, and another household member compensates for this illness, this will look like an anticipation response to an upcoming illness. Still, we believe that the results are suggestive of the time path of response, even if the magnitudes are hard to establish due to this issue.

The event study, presented in figure 2, is consistent with the possibility that some response to the illness of another worker in the household continues into the next week. For instance, conditional on lagged and lead effects, men are 7.9 percentage points more likely to work in weeks in which another family member is unexpectedly ill, and 7.6 percentage points more likely to work in the week after a family member is unexpectedly ill (P = 0.13). The estimated effect of another family member missing work next week (despite having planned to work that week) on men's contemporaneous labor supply, by contrast, is close to zero and statistically insignificant. A similar pattern emerges on the intensive margin, although the lagged effect of an illness is closer to zero and further from statistical significance (P = 0.46 in the specification for days of work, and P = 0.38 in the specification for hours).

[15] This interpretation of the coefficients in this graph diverge slightly from a traditional event study design, where the coefficients shown give treatment effects relative to a time period before the event (and the leads and lags are included in the estimation). Instead, because many respondents face multiple "treatments" (illness of other workers in their household), the coefficients in figure 2 show effects in the week before, during, and after the illness of another household member, relative to weeks in which there was no illness in that week, or the weeks before and after.

Interestingly, there is evidence that women show anticipation effects (though we highlight the caveat that their response is not statistically different from men's): summing the effect on men and the additional effect on women, we find that a woman works 0.46 more days (P = 0.098) and 6.4 more hours (P = 0.017) in weeks in which a household member will unexpectedly miss the upcoming week of work due to illness. We do not think these potential anticipation effects are necessarily problematic for the validity of our estimation strategy. Recall that if an illness begins at the end of a reporting period, contemporaneous response to that illness will look like anticipation, and figure 1 indicates that 50% of the illnesses of women and 30% of the illnesses of men that involve missing at least a day of work last longer than 7 days. It is then possible that another family member starts feeling ill one week (and may or may not stay home from work) and the family begins to compensate for the anticipated lost income. This pattern also fits with our hypothesis that women's response is dampened by caregiving duties; they may increase their labor supply when another family member starts feeling ill but does not yet need caregiving.

Table A8 then turns to workers's anticipation or continued responses to their own illness. Panel A confirms that there is minimal change in a respondent's average labor supply during weeks in which the worker him/herself reports an unexpected illness the next week. Panel B similarly finds that there is little net change in a worker's labor supply in weeks after she or he was unexpectedly ill. Thus, while workers appear to do some adjustment of their labor supply in response to other household member's oncoming or past illnesses, their own upcoming illness or recovery does not seem to be a relevant factor in determining labor supply.

3.2 Heterogeneity in individual-level outcomes

Table 3 examines the heterogeneity behind this average effect. In particular, we test several mechanisms that economic theory predicts would affect households' need or ability to use labor supply to respond to illness shocks. To begin, in table 3 we test whether workers in poorer households display greater increases in labor supply than workers in wealthier households. If so, this could either be because wealthy households have fungible savings that they can access to smooth consumption after short-run shocks, because wealthy households tend to be better integrated into risk sharing networks (Fafchamps 1992; de Weerdt 2004), or because it is easier to increase hours or send a substitute household member in the type of work done by workers in less wealthy households.

We indeed find some evidence – albeit not always statistically significant at traditional levels – that males in wealthier households are less likely to increase labor supply when another worker in their household is unexpectedly ill: a one standard deviation increase in assets is associated with 0.31 fewer days worked by a man in response to an illness shock ($P = 0.17$) and 2.9 fewer hours ($P = 0.15$). This heterogeneity is entirely driven by men; there is no evidence that heterogeneous effects by wealth underlie the net zero effect of the illness of a household member on women's labor supply. Columns 4 through 6 show that the same broad pattern occurs when using the average education of adults in the household as an alternate measure of socioeconomic status.

In table 4, we look within the household to test whether members with greater absolute earnings potential (as proxied by a dummy for the household member with the highest baseline earnings in the household) or greater comparative advantage in working (as proxied by a dummy variable for the household member with the highest usual hours of work in the household as reported at baseline) drive the response to illness shocks.[16] A male worker who is the highest earner in the household works 0.76 days and 7.6 more hours in response to the illness of another worker compared to another male. The results with usual hours of work lose statistical significance at conventional levels, but are still large quantitatively and point in the same direction as the earnings results.

Again, there is no differential effect for women who are the highest wage earners or have the highest usual hours of work (as reported in the baseline survey) in their households. This is not because too few women report the highest earnings or usual hours of work in their households to give us the power to detect these effects. Indeed, table A9 shows the joint distribution of gender and status as the highest earner and member with the longest usual hours of work in the household among the individuals employed at baseline. While it is more common for men to be the highest earners or have the most usual hours of work in the household – mirroring the result in table 1 that men on average have somewhat larger average hours of work and greater earnings than women – 42 percent of women are the highest earners in their household and 48 percent of women have the highest usual hours of work.[17] Instead, it appears that even (relatively) high-earning women have caregiving and other duties around the home that prevent them from increasing their labor supply when another worker is ill.

We now turn to another dimension of heterogeneity: risk aversion. The more risk averse an individual, the more he or she will dislike fluctuations in consumption, and thus, the greater the incentive to increase labor supply in order to smooth consumption. Survey respondents

[16] Table O1 in the online appendix (http://faculty.washington.edu/rmheath/onlineappendix_HMR.pdf) shows that these results are robust to alternate measures of hours and earnings, namely, to a dummy variable for above median hours/earnings within the household, and to the ratio of the respondent's hours/earnings to the household average.
[17] When considering only the sample of households with two or more employed workers at baseline (within which the sole employed worker is not automatically the highest earner or has the highest usual hours of work at baseline), the percentages naturally drop, but are still non-trivial: 37 percent of women have the highest regular hours of work and 30 percent of women are the highest earners.

participated in an incentivized risk game with six choice options ranging from 3 cedis for sure (3 cedis = $1.26 at the time of the survey) to 12 cedis with probability 0.5 and no payout with probability 0.5; the top left panel of figure 3 depicts the distribution of responses by men and women. Figure 3 then displays estimates of equation (1) with the effect of $Other\ Worker\ Ill_{ijct}$ allowed to vary by the risk chosen.[18] The labor supply response is driven primarily by men who chose the sure payout of 3 cedis. These men are 27 percentage points more likely to work in weeks in which another household member is ill,[19] and work an extra 1.5 days and 16 hours. There is also some suggestive, though not statistically significant, evidence of a response among the most risk averse women. Such women are 11 percentage points more likely to work (P = 0.19) during weeks in which another worker has an illness shock. That said, their smaller overall response in terms of hours and days worked suggests a potential countervailing effect, possibly because these women are also more likely to be caregivers.

Finally, we conclude our individual-level results by examining heterogeneity along several dimensions that could potentially matter for determining workers' labor supply responses to illness, but do not seem to be strong determinants of males' labor supply responsiveness to illness shocks in our sample. Table 5 examines heterogeneity by the job characteristics of a respondent's primary job at baseline. We first look for differential effects among those who were self-employed at baseline (70 percent of employed women and 48 percent of employed men), and those wage workers whose pay is irregular (22 percent of male wage workers and 15 percent

[18] The estimated coefficients used to construct these figures are given in table O2 in the online appendix.
[19] Some summary statistics help contextualize this very large effect: men who are the most risk averse and employed at baseline work in 96 percent of weeks in which another household member is ill, compared to 76 percent of weeks without the illness of another worker in the household. While the week dummies and controls for number of household members planning to work dictate that this difference is not precisely this treatment effect, the large difference that also appears in the raw data suggests that the effect is not an artifact of our particular estimation strategy.

of female wage workers).[20] Overall, we find only small and statistically insignificant evidence of differential increases among male self-employed workers, and essentially no difference between male wage workers with and without regular pay. While self-employed women also do not display a differential responsiveness to illness shocks, women in irregular wage work do display evidence of compensatory behavior; they work 0.86 more days and 5.6 more hours in weeks when another worker is unexpectedly ill.

We now turn to workers who work close to home, as defined by whether the work is done in the same enumeration area in which the respondent lives, which applies to 67 percent of women employed at baseline and 51 percent of men. We again find no differential responsiveness among men, but large point estimates for women. For instance, women who work far away from home work an estimated 7.2 fewer hours in weeks with a household member's illness than without an illness (P = 0.11); women who work close to home have if anything a slightly positive hours response. (The P-value of the difference in their response and that of women working far away from home is 0.06.) These results accord with our hypothesis that caregiving is a countervailing force that explains the net zero effect on women if women who work far from home find their jobs harder to combine with caregiving duties.

One possible explanation for the lack of strong effects by job type among males is that workers in a wide variety of jobs have flexibility to change their hours of work if they so desire (either through increased hours in their main job or in a secondary job). We provide ancillary evidence for this hypothesis by testing for differences across job type in the mean absolute within-worker deviation in hours worked by week over the course of the survey (that is,

[20] Namely, we consider as regular wage workers those who listed frequency of pay as every week, every two weeks, or every month. The remaining workers, whose pay we classify as irregular, listed responses such as daily or "each time the job is finished."

$\sum_{t=1}^{10} \left| hours_{ijt} - \overline{hours}_{ij} \right|$). The results, given in table A10, suggest that week-to-week hours vary considerably, even among workers whose primary jobs may not be characterized as flexible by standard definitions. While fluctuations in hours worked may also reflect changes in labor demand, these changes suggest that it is at least possible to change hours from week to week.

While the similar level of variation in hours between wage and self-employed workers may seem surprising at first, recall that the majority of wage work is plausibly informal. This is true for both those paid regularly and irregularly: specifically, 61 percent of wage workers with irregular pay at baseline and 66 percent of wage workers with regular pay are in the service sector, where there is presumably flexibility to extend hours to meet demand, or devote extra time to work to increase demand via advertising. To provide further reassurance that the similar within-worker deviation in hours is not an artifact of noise in the data, we examine between-worker variation in hours in the 2013 GHUPS round and the baseline of the high-frequency data we collect. Figure A2 shows that the distribution of hours worked look similar across wage and self-employment in both surveys, and there is no evidence of stronger bunching around benchmarks like 40 hours a week among wage workers.[21]

Lastly, table A11 examines potential differences in responsiveness to illness shocks by household composition. While it is possible that households with more potential alternative caregivers free up employed adults from caregiving – thereby allowing them to increase their labor even more than adults in other households – there is no evidence of differentially increased labor supply by either men or women in households with elderly members or working age adults not in the labor force. By contrast, men in households with more children are more likely to

[21] Moreover, in the high frequency baseline, the mean absolute deviation across workers is not statistically different between wage and self-employed for either men or women, and while it does differ in the 2013 GHUPS, the differences are statistically significant but relatively small in magnitude (3.3 hours for men and 1.4 hours for women).

respond, and women in households with more children display a less negative response (although neither difference is statistically significant). Panel D does provide some evidence that the labor supply response to illness shocks among male workers is driven primarily by married workers.

3.3 Evidence of the main mechanism: Workers earn more when they work more

A key assumption behind the mechanism that workers increase labor supply to compensate for income losses due to the illness of other household members is that workers actually earn more when they work more hours. For self-employed workers, this assumption is a priori believable, and we can also check this in our data by regressing weekly earnings on hours of work, conditional on worker fixed effects. Table A12 confirms this relationship: a self-employed worker earns 2.5 additional cedis for every hour that she or he works, compared to an average total earning of self-employed workers of 116 cedis.

For wage workers, we must assume this relationship; recall that section 2.4 explains that we did not directly ask wage workers their earnings in the high frequency survey. So, if wage workers earn a fixed salary regardless of their hours, the premise that they work more to make up the lost income from other workers would not apply. However, many wage workers are in customer-facing jobs – 65% percent of wage workers are in services and 14% of wage workers are in retail – where we believe it is plausible that they can work and earn more if they desire.

Moreover, wage workers do work more in response to the illness of other workers in their household: the coefficient on $Other\ Worker\ Ill_{ijct} \times Self\ Employed_{ijc}$ in table 6 is positive, but small in magnitude. If wage workers do not actually earn more when they work more, a key question is why they do actually work more. While we argue that the ability to increase take-home pay is the most plausible reason for increased labor supply among wage workers in response to the illness of others in their household, we acknowledge that other explanations are possible. For instance, perhaps wage workers fill in for each other in order to make sure time-sensitive work gets done. Even if one of these alternate mechanisms is behind the labor supply result for wage workers, our results nonetheless provide new insight linking illness to labor supply in low-income countries.

4. Household-level outcomes

We now examine the overall effects of a member's illness-related absence on household level income and labor supply, including both the direct effects of the missed work and the compensatory responses of other household members documented in the previous two subsections. We also look separately at households for whom these compensatory responses are likely to be strongest – those with two or more earners at baseline[22] and those with at least one male worker – and households in which there are no male earners or a female is the highest earner, given the minimal net response by females shown in table 2.

In each case, we conduct a back-of-the-envelope exercise that estimates the fraction of the expected income loss of the sick individual covered by the household income inclusive of compensatory behavior. Specifically, we compute the expected income loss of a sick individual in a specific class of households by taking the average usual reported income from the baseline survey of individuals in those households who are unexpectedly sick over the course of the survey. We then compute the fraction of the expected loss covered by the coefficient estimate

[22] These are also the households providing the majority of the identifying variation in the individual-level results, since a worker in the regression would need to have another family member who was planning to work in order to have identifying variation in the *Other Worker Ill* variable. While we estimate equation 1 on the whole sample of workers employed at baseline (workers who are the only worker in their family over the entire survey help to identify the week fixed effects), results are almost identical if we use only the sample of workers in households with two or more earners at baseline.

from the estimation results (which reflects the actual loss, inclusive of compensatory behavior). For instance, column 1 reports that across all households, the average income of males who are sick over the course of the survey is 105 cedis. The coefficient of -82 on $Worker\ Ill_{jct}$ indicates that (105-82)/105 = 22 percent of the expected income loss from males is compensated. Note that it is plausible that the actual loss is even bigger than the expected loss (resulting in a negative fraction of the expected loss compensated), if the household also loses income from a caregiver, as is the case for women across all households (also shown in column 1).

Column 1 of table 6 indicates that, across all households, total household earnings fall by 82 cedis when a man misses work because of illness and by 70 cedis when a woman does so.[23] The hours responses are more precisely estimated and show a larger drop of 29 hours from male illness, versus 16 hours after a female illness. While the effect of male and female illness on income is similar across the whole sample, re-estimating using sub-samples of households more likely to show compensatory behavior highlights the role of this compensation in net household income. In particular, in households with two or more earners at baseline, a man's illness results in an income decrease of 96 cedis, and a woman's illness decreases income by 44 cedis (though the difference is not statistically significant at traditional levels, P = 0.21). The differential reduction in hours after a female illness is also larger – a 22 hour smaller decrease after a woman's illness.

Evidence of compensation emerges when we focus on households with male earners. For households with at least one male earner, a male illness results in an income loss of 90 cedis, while female sickness results in a loss of only 35 cedis. Indeed, while the loss in male income is

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[23] Table O3 in the online appendix shows that the income results are almost identical if winsorized at either the 1st and 99th percentiles or the 5th and 95th percentiles, providing reassurance that outliers are not driving the income results.

even larger than the expected loss due to the sick male's income (plausibly due to caregivers' missed work as well), 39% of the expected income loss from a woman's illness is compensated through labor supply response. In households with two or more male earners, a male illness remains very costly, at 131 cedis, while a woman's illness only results in a net loss of 1 cedi: 99% of the expected loss is compensated. Meanwhile, a man's illness leads to 41 fewer labor hours, while a woman's leads to only 8 fewer (P = 0.30).

By contrast, a woman's illness is quite costly in households without male earners at baseline; a female illness leads to an income loss of 115 cedis, which is greater than the predicted income loss based on baseline earnings. Similar effects occur in households in which a woman is the highest earner at baseline. In these households, a male illness has an insignificant effect on household income, while a woman's illness leads to an average loss of 97 cedis. In these households, the compensation for the male's income loss is complete, while now it is the woman's illness that leads to a greater income loss than predicted based on her baseline earnings. Indeed, woman's earnings are not substantially higher in these households (they are actually lower than women's earnings in households with two or more male earners), so the difference in total effect appears due to compensation, not baseline earnings capacity. On a similar note, the hours response is not substantially larger than for the overall sample (19 fewer total hours in households with no male earners, and 17 hours in households in which a female is the highest earner), suggesting that the costliness of female illness is due to the value of those uncompensated hours rather the total hours. However, we highlight the caveat that income is inferred based on the hours of work for wage workers.

To further examine compensatory behavior in households in which women are high earners, we re-estimate equation 1 on the sample of men and women in households in which women are the primary earners. Table 3 showed that women who are high earners are no more likely than other women to work in response to the illness of another household member, and table A13 adds the result that males in these households compensate less on the extensive margin than other males: they are not on average any more likely to work in weeks in which another household member is ill. By contrast, there is a positive (though statistically insignificant) intensive margin effect – they work an additional 4.6 hours per week - which is very similar to the overall response by males. Still, given the illness of the main wage earner, the net effect on income of a female illness suggests that this compensation is unable to keep a female illness from being particularly costly.

5. Conclusion

In an environment in which households have limited mechanisms to smooth consumption -- specifically, urban Ghana --we document that men increase their labor supply in response to the unexpected illness of a worker in their household. In particular, men are 8.8 percentage points more likely to work at all – and work 0.39 more days and 4.7 more hours – during weeks in which another adult in the household unexpectedly misses work for the entire week due to illness or injury. The characteristics of the worker's primary job do not strongly affect labor market response. This suggests that a dichotomy between rigid wage work and flexible self-employment may not be salient in urban labor markets in a developing country context.

Gender, by contrast, is an important determinant of compensatory behavior. The fact that even high-earning women do not compensate for the illness of other workers suggests that their value as caregivers is even higher. This could help explain some of the gender difference in earnings in developing countries. Caregiving responsibilities may prevent women from taking advantage of labor market opportunities more broadly.

Even in a developing country like Ghana, with universal health insurance, lost labor income and the (uninsured) financial cost of treatment still appear sufficiently sizeable to prompt households to increase labor supply in response to illness shocks. Labor supply responses are particularly strong in low socio-economic status households, suggesting that as incomes rise, households have better access to alternative income smoothing mechanisms, which reduce the pressure on household members to work extra hours to cover income losses. For poor households that lack these smoothing mechanisms, however, flexible labor options are an important coping mechanism for dealing with unanticipated illness shocks.

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Appendix A: Calculating Earnings

Self-employment income was calculated in the weekly survey by summing the responses to the questions “How much of that money was for work you did over the past 7 days?” (the follow-up to the question “How much money have you received over the past 7 days?”) and “How much more do/did you expect to receive for the work you did over the past week? Please do not include money that you received over the past week.” Reported costs were then subtracted from these revenues, using the answer to the question “How much were the costs for only the past 7 days (if the costs are for a machine for example, only include the cost of using the machine for a week)”, which was the follow-up to the question “Did you have any costs for goods or equipment that were needed for your work over the past week?”.

Wage employment income was calculated by multiplying days of work by the respondent’s usual daily wage rate, as calculated from the baseline reports of their usual weekly pay “On average, how much do you earn (or, if in kind, what is the value of what you earn) in your primary job, in a week?” divided by their usual days of work, given by their response to the question “How many days do you work in your primary job during a normal week?” unless the respondent answered yes to the question “Since the last interview, did the way that you calculate the amount of work you get paid for change?” If so, they were asked for the earnings in this new job in a normal week, and this rate was multiplied by the number of days worked that week to the calculate earnings. Note that this calculation means that workers who are paid less frequently than on a weekly basis – 73 percent of wage workers – are assigned the fraction of their weekly pay that corresponds to the number of hours worked per week.

Figure 1: Length of illness spells

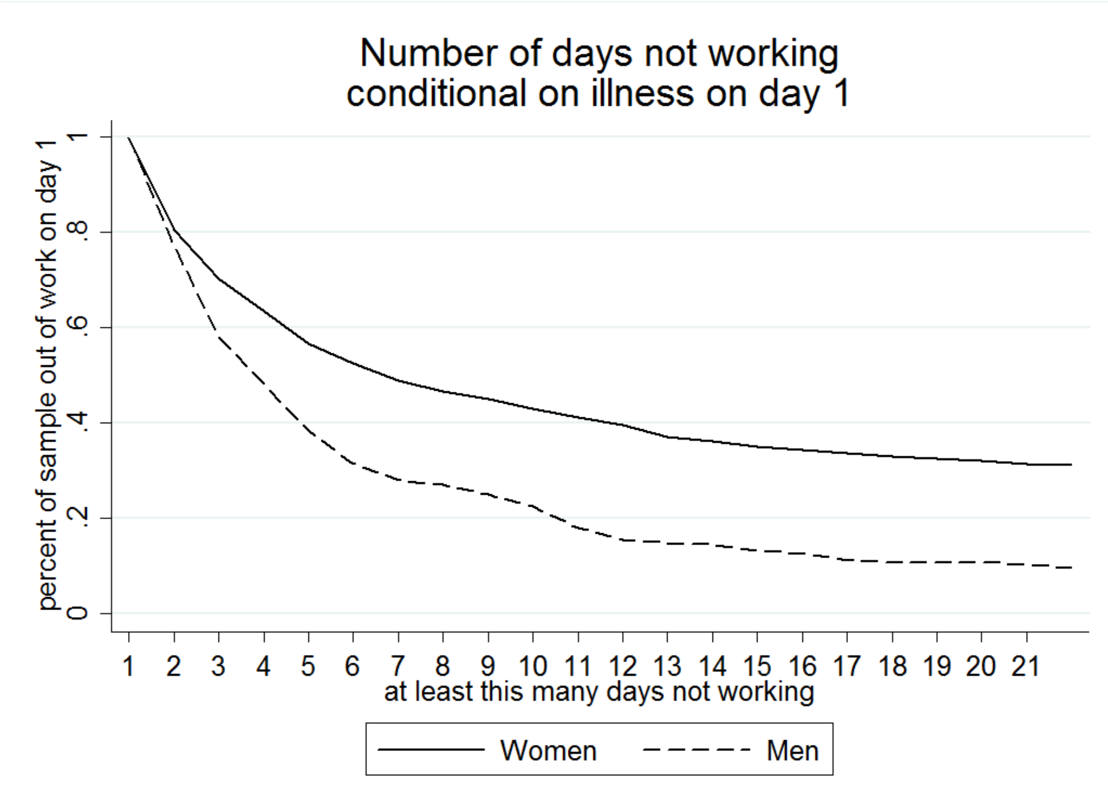
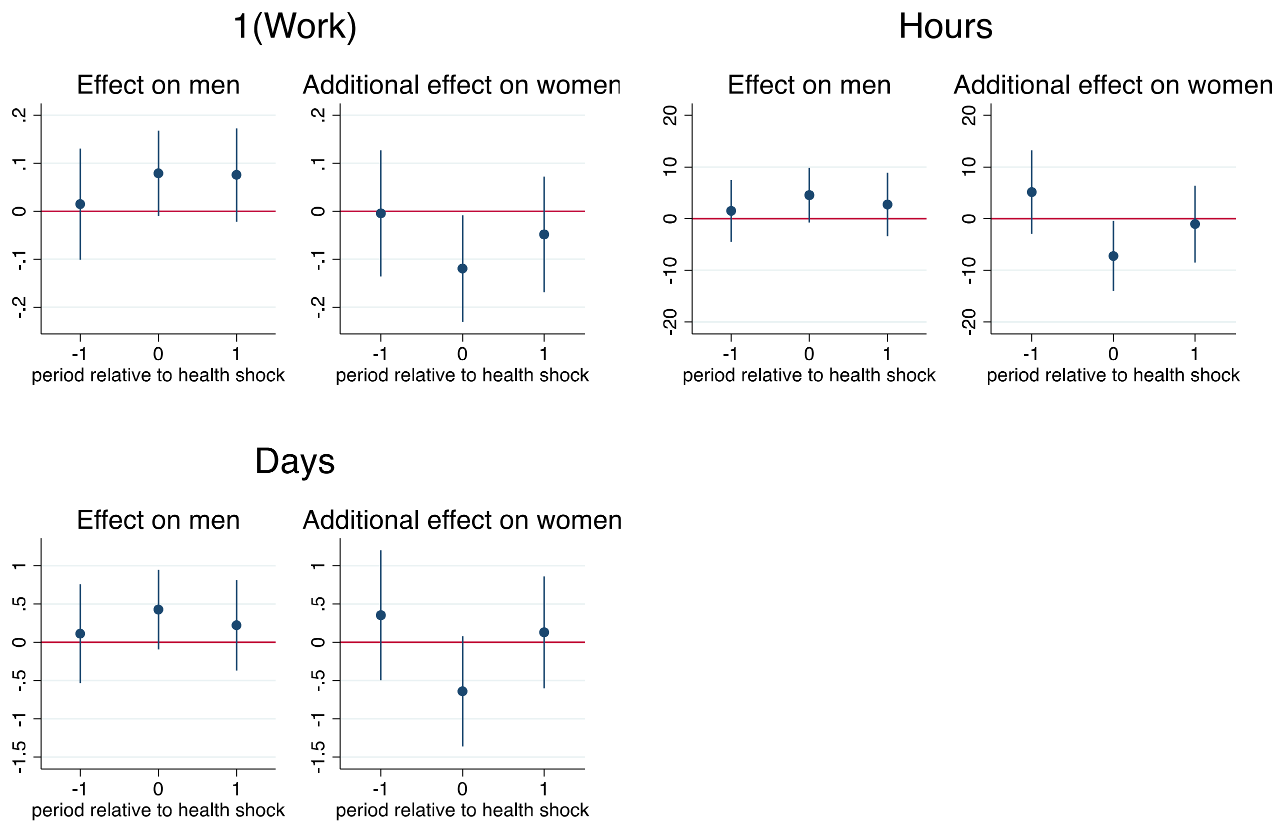
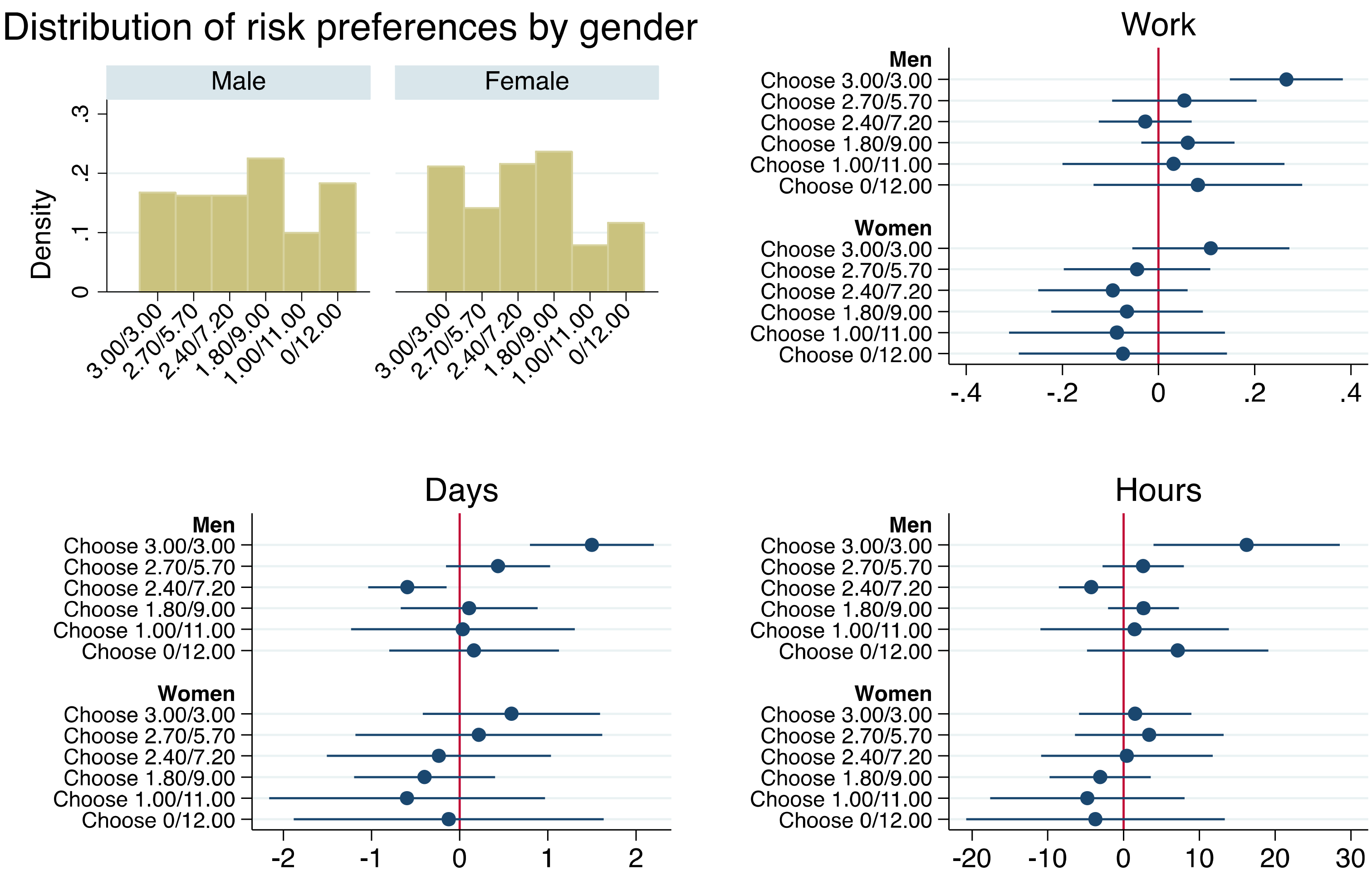


Figure 2: Event study: lagged, contemporaneous and lead effect of household worker sickness



Graph on left shows coefficient from the Other Worker Ill variable.
Graph on right shows the interation term Other Worker Ill X Female.

Figure 3: Heterogeneity by risk aversion



Estimates graphed are the coefficient of *Other Worker Sick* interacted with the choice of each gamble
Payoffs in Ghanaian cedis; in fall 2013, 1 Ghanaian cedi = approximately 0.42 USD

Figure A1: Event study: lagged, contemporaneous and lead effects of household worker sickness (daily data)

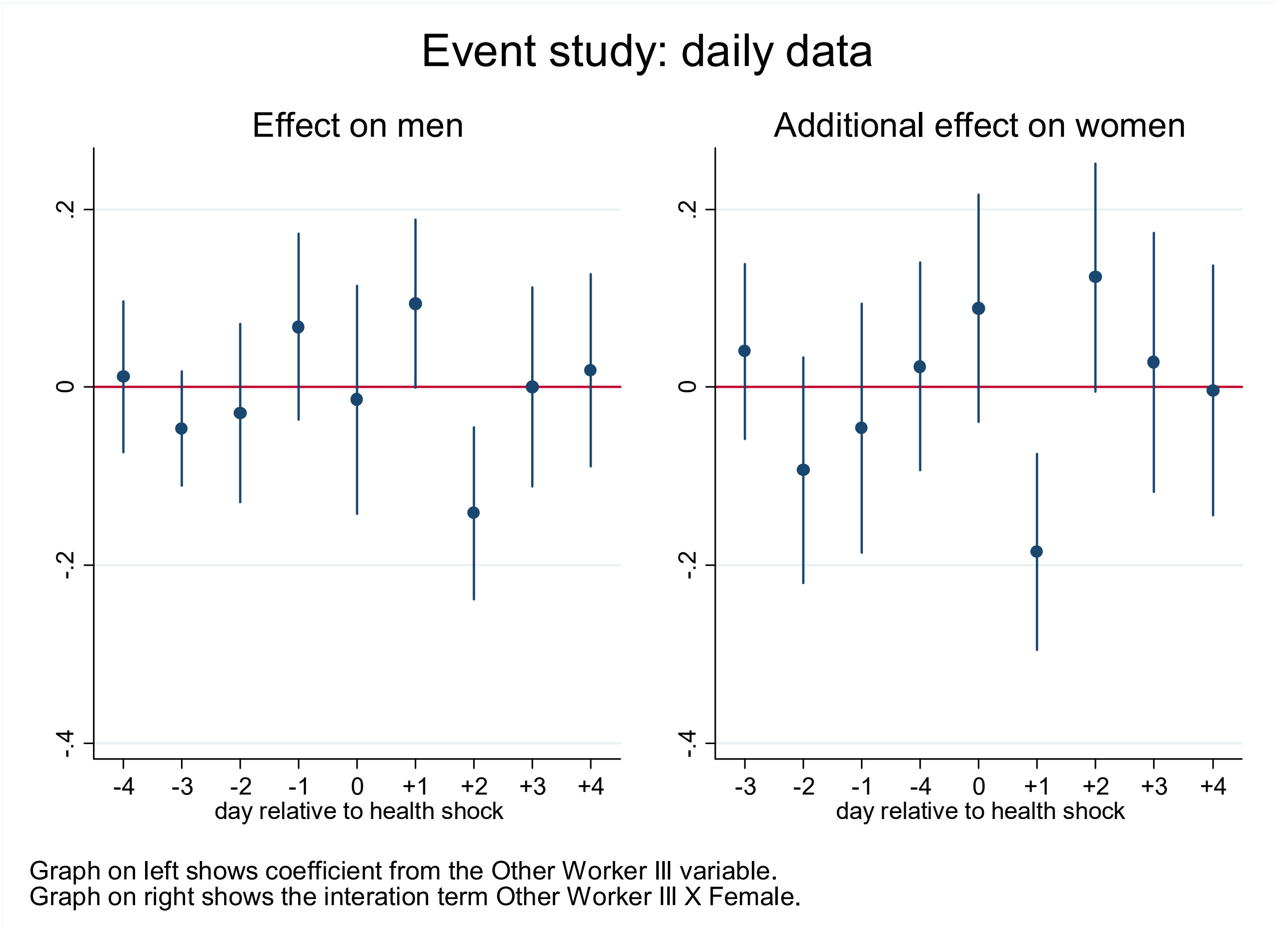
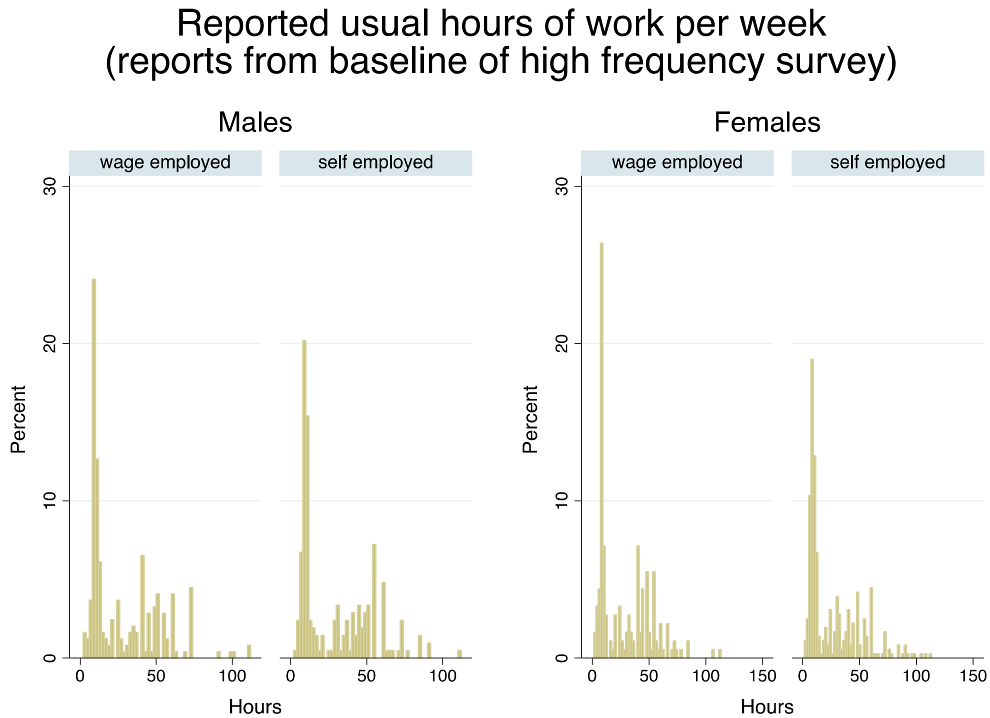


Figure A2: Between-worker variance in hours worked



Panel B: Hours of work last week from 2013 GHUPS round

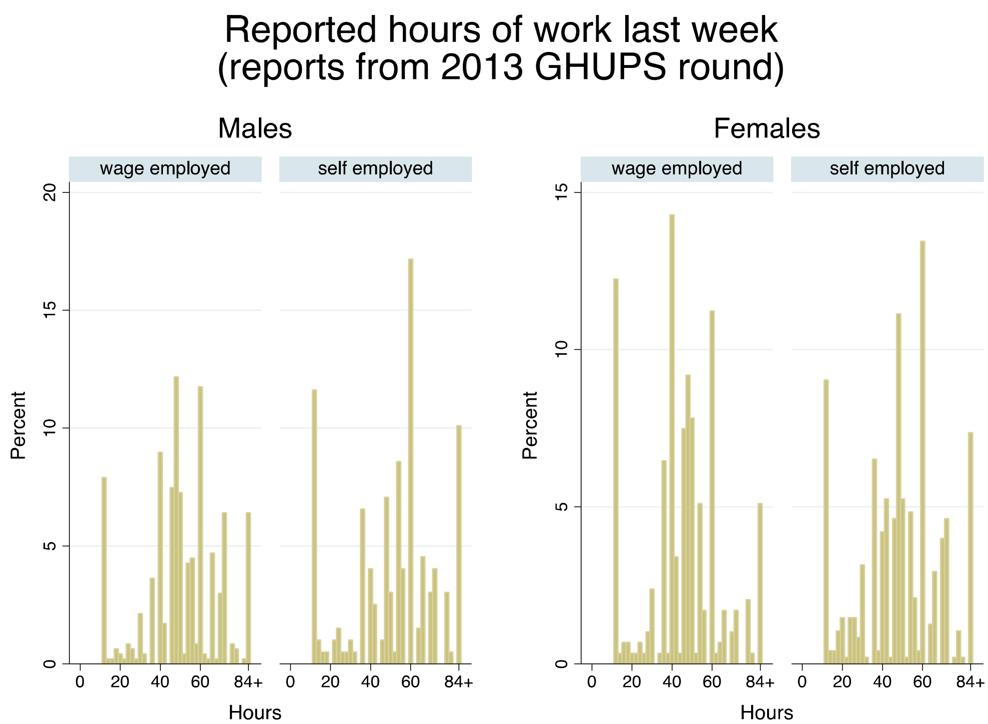


Table 1: Summary Statistics

	Males	Females
Baseline Characteristics		
age	33.94	36.01
education (years)	11.18	9.35
married	0.446	0.506
number of children	1.54	2.31
total adults age 18 - 65 in household	5.60	6.14
employed	0.718	0.657
conditional on being employed…		
self employed	0.482	0.697
usual hours of work	51.10	49.42
usual weekly earnings (cedis)	162.36	94.98
Outcomes during the High-Frequency Survey		
full sample		
missed work due to own unexpected illness last week	0.020	0.024
missed work due to caretaking illness last week	0.000	0.013
missed work due to unexpected illness (own or caretaking) last week	0.020	0.037
ever missed a week of work due to own unexpected illness	0.109	0.134
ever missed a week of work due to caretaking	0.000	0.030
ever missed a week of work due to unexpected illness (own or care)	0.109	0.163
conditional on being employed at baseline…		
missed work due to own unexpected illness last week	0.025	0.031
missed work due to caretaking illness last week	0.000	0.020
missed work due to unexpected illness (own or caretaking) last week	0.025	0.051
ever missed a week of work due to own unexpected illness	0.136	0.162
ever missed a week of work due to caretaking	0.000	0.046
ever missed a week of work due to unexpected illness (own or care)	0.136	0.207
worked in the past week (full sample)	0.643	0.556
worked in the past week (conditional on employment at baseline)	0.850	0.809
conditional on working last week…		
days of work	5.27	5.30
hours of work	47.47	45.32
earnings (cedis)	167.72	107.447
Number of individuals	266	367
Number of observations	2,433	3,345

Notes: employed = 1 in the baseline if respondent reports that s/he has "stable work done for pay or gain and expect to continue doing it for next three months" OR "any work at all that you do for pay or gain and that you do regularly"? Ill the past week = 1 if a respondent reported missing work for an entire week in which he or she had planned to work and the reported reason was injury/illness. The 2013 exchange rate was 0.42 cedis to 1 US dollar.

Table 2: Effects of a Worker's Unexpected Illness on the Labor Supply of Other Household Members

Dependent Variable	1(Work)	Days worked	Hours worked
Panel A: Overall effects			
Other worker ill	0.013	0.130	1.618
	[0.027]	[0.164]	[1.482]
Observations	3,951	3,948	3,948
R-squared	0.501		
Panel B: Effects by gender of responder			
Other worker ill	0.088**	0.394*	4.715**
	[0.036]	[0.237]	[2.332]
Other worker ill X Female	-0.131**	-0.496	-5.718
	[0.052]	[0.327]	[3.494]
Mean dependent variable	0.807	4.279	37.660
Observations	3,951	3,948	3,948
R-squared	0.502		

*Notes: Other worker ill = 1 if another household member reported missing work for an entire week in which s/he was planning to work and the reason for missing work was injury/illness. Sample includes respondents employed at baseline. All specifications include individual fixed effects. Column 1 is estimated by OLS and columns 2 and 3 are estimated using least squares with trimming to account for censoring of the dependent variable (Honore, 1992). Regressions include week-of-interview dummies interacted with gender, week-of interview dummies interacted with city, and controls for the number of household members planning to work in that round interacted with gender. Standard errors in brackets, clustered at the household level: *** p<0.01, ** p<0.05, * p<0.1.*

Table 3: Heterogeneous Effects by Household-level Socioeconomic Status

Dependent variable	1(Work)	Days worked	Hours worked	1(Work)	Days worked	Hours worked
Other worker ill	0.075**	0.294	3.354	0.226**	1.696**	12.939*
	[0.032]	[0.259]	[2.216]	[0.112]	[0.804]	[6.748]
Other worker ill X Female	-0.131***	-0.380	-4.357	-0.172	-1.203	-4.761
	[0.047]	[0.327]	[3.101]	[0.179]	[1.177]	[8.893]
HH Assets at Baseline X Other worker ill	-0.030	-0.310	-2.862			
	[0.033]	[0.225]	[1.974]			
HH Assets at Baseline X Other worker ill	0.004	0.303	2.876			
X Female	[0.049]	[0.260]	[2.528]			
HH Average Education X Other worker ill				-0.014	-0.134*	-0.842
				[0.011]	[0.077]	[0.625]
HH Average Education X Other worker ill				0.003	0.064	-0.260
X Female				[0.020]	[0.129]	[0.982]
Net effect on Male 1 sd below mean	0.108	0.63	6.452	0.121	0.715	6.769
P-value	0.029	0.029	0.014	0.006	0.034	0.032
Net effect on Male 1 sd above mean	0.045	-0.013	0.519	0.045	0.006	2.312
P-value	0.299	0.972	0.885	0.281	0.986	0.445
Net effect on Female 1 sd below mean	-0.028	-0.078	-1.019	-0.031	-0.022	0.100
P-value	0.506	0.738	0.648	0.434	0.926	0.964
Net effect on Female 1 sd above mean	-0.081	-0.093	-0.990	-0.092	-0.394	-5.735
P-value	0.126	0.761	0.718	0.279	0.412	0.258
Mean dependent variable	0.807	4.279	37.660	0.807	4.279	37.660
Observations	3,769	3,766	3,766	3,951	3,948	3,948
R-squared	0.512			0.507		

*Notes: Other worker ill = 1 if another household member reported missing work for an entire week in which s/he was planning to work and the reason for missing work was injury/illness. Sample includes respondents employed at baseline. Assets are measured by the first principal component from an index of household assets including bed, wall clock, watch, player, radio, tv, sewing machine, fan, air conditioning, fridge, freezer, gas stove, shovel, landline telephone, cell, bike, motorbike, car, computer, livestock, farm implements, generator, land; then normalized to have mean zero and standard deviation one. Column 1 is estimated by OLS and columns 2 and 3 are estimated using least squares with trimming to account for censoring of the dependent variable (Honore, 1992). Regressions include week-of-interview dummies interacted with gender, week-of interview dummies interacted with city, and controls for the number of household members planning to work in that round interacted with gender. Standard errors in brackets, clustered at the household level: *** p<0.01, ** p<0.05, * p<0.1.*

Table 4: Heterogeneous Effects by Absolute and Relative Earning Potential within Household

Dependent variable	1(Work)	Days worked	Hours worked	1(Work)	Days worked	Hours worked
Other worker ill	0.052	0.078	1.557	0.068	0.225	2.533
	[0.042]	[0.291]	[2.495]	[0.048]	[0.288]	[2.111]
Other worker ill X Female	-0.058	0.039	-2.632	-0.122	-0.477	-3.433
	[0.066]	[0.337]	[3.127]	[0.075]	[0.363]	[3.289]
Highest baseline earnings in household	0.083	0.760	7.549*			
X Other worker ill	[0.062]	[0.463]	[4.347]			
Highest baseline earnings in household	-0.202*	-1.389*	-7.254			
X Other worker ill X Female	[0.104]	[0.719]	[7.377]			
Highest usual hours of work in household				0.054	0.489	6.032
X Other worker ill				[0.068]	[0.512]	[5.760]
Highest usual hours of work in household				-0.024	-0.103	-6.212
X Other worker ill X Female				[0.113]	[0.657]	[7.469]
Net Effect on a Male w/ Highest Earn/Hours	0.135	0.838	9.106	0.122	0.713	8.565
P-value	0.007	0.007	0.006	0.009	0.069	0.068
Net Effect on a Female w/ Highest Earn/Hours	-0.124	-0.511	-0.780	-0.024	0.134	-1.079
P-value	0.081	0.259	0.875	0.706	0.607	0.950
Mean dependent variable	0.807	4.279	37.660	0.807	4.279	37.660
Observations	3,951	3,948	3,948	3,951	3,948	3,948
R-squared	0.507			0.507		

*Notes: Other worker ill = 1 if another household member reported missing work for an entire week in which s/he was planning to work and the reason for missing work was injury/illness. Sample includes respondents employed at baseline. Usual earnings and usual hours of work taken from reports in baseline survey. All specifications include individual fixed effects. Column 1 is estimated by OLS and columns 2 and 3 are estimated using least squares with trimming to account for censoring of the dependent variable (Honore, 1992). Regressions include week-of-interview dummies interacted with gender, week-of interview dummies interacted with city, and controls for the number of household members planning to work in that round interacted with gender. Standard errors in brackets, clustered at the household level: *** p<0.01, ** p<0.05, * p<0.1.*

Table 5: Heterogeneous Effects by Job Characteristics

Dependent variable	1(Work)	Days worked	Hours worked	1(Work)	Days worked	Hours worked
Other worker ill	0.074	0.273	2.599	0.119**	0.486	6.108*
	[0.058]	[0.325]	[3.750]	[0.047]	[0.305]	[3.477]
Other worker ill X Female	-0.115	-0.306	-5.248	-0.193**	-1.151**	-13.278**
	[0.111]	[0.597]	[6.189]	[0.085]	[0.539]	[5.957]
Self employed X Other worker ill	0.042	0.295	4.801			
	[0.087]	[0.478]	[5.295]			
Self employed X Other worker ill X Female	-0.047	-0.425	-3.088			
	[0.126]	[0.760]	[7.506]			
Irregular wage work X Other worker ill	-0.003	0.148	2.996			
	[0.081]	[0.617]	[5.675]			
Irregular wage work X Other worker ill	0.078	0.741	5.26			
X Female	[0.159]	[0.877]	[7.896]			
Work close to home X Other worker ill				-0.069	-0.181	-2.883
				[0.064]	[0.378]	[4.077]
Work close to home X Other worker ill				0.119	1.054*	12.337**
X Female				[0.098]	[0.630]	[6.401]
Net effect on Self Employed Male	0.116	0.568	7.400			
P-value	0.051	0.128	0.000			
Net effect on Self Employed Female	-0.046	-0.163	-0.936			
P-value	0.294	0.542	0.168			
Net effect on Irreg Wage Employed Male	0.071	0.421	5.595			
P-value	0.204	0.443	0.132			
Net effect on Irreg Wage Employed Female	0.190	0.856	5.607			
P-value	0.209	0.000	0.084			
Net effect on Male Working Close to Home				0.0499	0.305	3.225
P-value				0.295	0.29954	0.21324
Net effect on Female Working Close to Home				-0.0243	0.208	2.284
P-value				0.597	0.40728	0.29809
Mean dependent variable	0.807	4.279	37.660	0.807	4.279	37.660
Observations	3,951	3,948	3,948	3,951	3,948	3,948
R-squared	0.507			0.507		

*Notes: Other worker ill = 1 if another household member reported missing work for an entire week in which s/he was planning to work and the reason for missing work was injury/illness. All specifications include individual fixed effects. Sample includes respondents employed at baseline. Column 1 is estimated by OLS and columns 2 and 3 are estimated using least squares with trimming to account for censoring of the dependent variable (Honore, 1992). Work close to home = 1 if the worker reported during the baseline survey that s/he normally works "close to home". Regressions include week-of-interview dummies interacted with gender, week-of interview dummies interacted with city, and controls for the number of household members planning to work in that round interacted with gender. Standard errors in brackets, clustered at the household level: *** p<0.01, ** p<0.05, * p<0.1.*

Table 6: Net Effects of the Illness of a Worker on Household-Level Labor Outcomes

		Households with…				
Sample of households	all	2 + earners at baseline	0 male earners at baseline	1+ male earner at baseline	2+ male earners at baseline	HH in which woman is highest earner at baseline
			Panel A: Dependent Variable = Total household income			
Worker ill	-81.945***	-95.685**	-16.763	-89.743***	-131.140***	8.265
	[24.649]	[38.754]	[42.176]	[28.818]	[43.898]	[28.938]
Worker ill X Female ill	11.625	51.445	-98.06	54.586	130.164**	-104.956*
	[36.528]	[41.083]	[76.562]	[35.321]	[57.475]	[53.902]
Observations	2345	1268	889	1456	353	940
R-squared	0.544	0.577	0.557	0.532	0.52	0.538
Mean dependent variable	202.60	259.80	126.9	248.80	307.80	183.90
Overall effect of female illness	-70.320	-44.240	-114.8	-35.160	-0.976	-96.69
P-value	0.004	0.024	0.018	0.109	0.980	0.019
Expected male earnings loss from baseline	105.500	92.06	n/a	105.5	77.06	42.33
Fraction of expected loss compensated	0.224	-0.039	n/a	0.150	-0.702	1.195
Expected female earnings loss from baseline	49.040	50.07	40.06	57.4	67.5	53.68
Fraction of expected loss compensated	-0.434	0.116	-1.867	0.387	0.986	-0.801
			Panel B: Dependent variable = Total Household Labor Hours			
Worker ill	-28.569***	-38.751***	-13.503	-29.440***	-40.587***	-12.719
	[5.563]	[7.894]	[11.580]	[5.776]	[9.843]	[9.688]
Worker ill X Female ill	12.082*	21.880**	-5.375	13.971*	32.348***	-4.767
	[6.813]	[9.082]	[12.888]	[8.052]	[10.896]	[8.543]
Observations	2345	1268	889	1456	353	940
R-squared	0.797	0.751	0.744	0.783	0.719	0.815
Mean dependent variable	67.03	95.70	40.00	83.54	112.60	72.24
Overall effect of female illness	-16.490	-16.870	-18.880	-15.470	-8.24	-17.490
P-value	0.000	0.000	0.000	0.004	0.301	0.001

*Notes: Worker ill = 1 if a household member reported missing work for an entire week in which s/he was planning to work that week and the reason for missing work was injury/illness. Expected earnings loss from baseline is calculated by taking the average usual reported income from the baseline survey of individuals who are unexpectedly sick over the course of the survey. All specifications include household fixed effects, week of interview dummies interacted with city, and controls for the number of household members planning to work in that round. Standard errors in brackets, clustered at the household level: *** p<0.01, ** p<0.05, * p<0.1.*

Table A1: Effects of a Worker's Unexpected Illness on the Labor Supply of Other Household Members in the Daily Labor Supply Data

Dependent variable	1(Work)	Hours Worked
Other worker ill	-0.024	-0.147
	[0.035]	[0.343]
Other worker ill X Female	-0.001	-0.065
	[0.041]	[0.443]
Mean Dependent Variable	0.538	4.309
Observations	8,409	8,409
R-squared	0.417	

*Notes: Other worker ill = 1 if another household member reported missing work for a day in which s/he was planning to work and the reason for missing work was injury/illness. Sample includes respondents employed at baseline. All specifications include individual fixed effects and gender interacted with day-of-the-week dummies and week-of -interview dummies, week-of interview dummies interacted with city, a dummy for whether the report was for the day before yesterday interacted with gender, and a control for the number of household members planning to work in that round interacted with gender. Cape Coast dropped due to a small number of respondents in the daily sample. Column 1 is estimated by OLS and column 2 is estimated using least squares with trimming to account for censoring of the dependent variable (Honore, 1992). Standard errors in brackets, clustered at the household level: *** p<0.01, ** p<0.05, * p<0.1.*

Table A2: Effects of a Worker's Unexpected Illness on the Labor Supply of Other Household Members, Based on Characteristics of the Absent Worker

Dependent Variable	1(Work)	Days worked	Hours worked
Panel A: Absent Work is Ill Him/Herself vs Caretaking			
Other worker ill him/herself	0.077**	0.344*	4.299**
	[0.037]	[0.236]	[2.227]
Other worker caretaking	0.192***	0.896	8.808
	[0.060]	[0.671]	[6.827]
Female X Other worker ill him/herself	-0.304**	-1.422*	-11.745*
	[0.134]	[0.908]	[7.885]
Female X Other worker caretaking	0.192	1.026	6.640
	[0.142]	[0.925]	[8.323]
P-value for equal responses: Males	0.120	0.400	0.482
P-value for equal responses: Females	0.101	0.170	0.209
Mean dependent variable	0.807	4.279	37.660
Observations	3,951	3,948	3,948
R-squared	0.507		
Panel B: Gender of Ill Worker			
Other worker ill	0.037	0.325	3.468
	[0.063]	[0.461]	[3.776]
Other worker ill X That worker is female	-0.039	-0.231	-4.297
	[0.079]	[0.572]	[5.539]
Female X Other worker ill	-0.077	-0.556	-7.764
	[0.111]	[0.558]	[4.991]
Female X Other worker ill X That worker is female	-0.074	0.094	3.005
	[0.122]	[0.672]	[6.592]
P-value for equal responses: Males	0.795	0.825	0.840
P-value for equal responses: Females	0.962	0.655	0.294
Mean dependent variable	0.807	4.279	37.660
Observations	3,951	3,948	3,948
R-squared	0.507		

Panel C: Employment of Ill Worker			
Other worker ill	0.068	0.454	5.080
	[0.061]	[0.381]	[3.430]
Other worker ill X That worker is self-employed	0.029	-0.072	-0.434
	[0.065]	[0.553]	[5.552]
Female X Other worker ill	-0.136	-0.801	-7.966
	[0.098]	[0.510]	[5.235]
Female X Other worker ill X That worker is self-employed	0.012	0.476	3.450
	[0.107]	[0.729]	[7.449]
P-value for equal responses: Males	0.747	0.534	0.502
P-value for equal responses: Females	0.606	0.413	0.526
Mean dependent variable	0.807	4.279	37.660
Observations	3,951	3,948	3,948
R-squared	0.507		

*Notes: Other worker ill = 1 if another household member reported missing work for an entire week in which s/he was planning to work and the reason for missing work was injury/illness. Sample includes respondents employed at baseline. All specifications include individual fixed effects. Column 1 is estimated by OLS and columns 2 and 3 are estimated using least squares with trimming to account for censoring of the dependent variable (Honore, 1992). Regressions include week-of-interview dummies interacted with gender, week-of interview dummies interacted with city, and controls for the number of household members planning to work in that round interacted with gender. Standard errors in brackets, clustered at the household level: *** p<0.01, ** p<0.05, * p<0.1.*

Table A3: Effects of a Worker's Unexpected Illness on the Labor Supply of Other Household Members Who are Not Employed at Baseline

Dependent Variable	1(Work)	Days worked	Hours worked
Other worker ill	-0.032	-0.061	-1.470
	[0.042]	[0.998]	[8.005]
Other worker ill X Female	0.007	-0.926	-0.396
	[0.056]	[1.477]	[14.532]
Mean dependent variable	0.129	0.671	5.420
Observations	1,823	1,820	1,820
R-squared	0.736		

*Notes: Other worker ill = 1 if another household member reported missing work for an entire week in which s/he was planning to work and the reason for missing work was injury/illness. Sample includes only respondents not employed at baseline. All specifications include individual fixed effects. Column 1 is estimated by OLS and columns 2 and 3 are estimated using least squares with trimming to account for censoring of the dependent variable (Honore, 1992). Regressions include controls for the number of household members planning to work in that round interacted with gender. Standard errors in brackets, clustered at the household level: *** p<0.01, ** p<0.05, * p<0.1.*

Table A4: Correlation between labor supply of family members

Dependent Variable	1(Work)	Days worked	Hours worked
Other household members working	-0.007	-0.09	-0.831
	[0.021]	[0.099]	[1.159]
Other household members working X Female	0.033	0.343***	4.265***
	[0.027]	[0.127]	[1.320]
Mean dependent variable	0.86	4.704	42.559
Observations	2,487	2,487	2,487
R-squared	0.533		

Notes: Other worker ill = 1 in a given week if another household member reported missing work that entire week (if s/he was planning to work that week) and the reason for missing work was injury/illness. Self ill next week/previous week = 1 if that worker reported missing work that entire next week (if s/he was planning to work that week) and the reason for missing work was injury/illness. Sample includes respondents employed at baseline. Regressions include individual fixed effects, week-of-interview dummies interacted with gender, week-of interview dummies interacted with city, and controls for the number of household members planning to work in that round interacted with gender. Column 1 is estimated by OLS and columns 2 and 3 are estimated using least squares with trimming to account for censoring of the dependent variable (Honore, 1992). Standard errors in brackets, clustered at the household level.

Table A5: Effects of a Worker's Unexpected Illness on the Labor Supply of Other Household Members, with Enumeration Area X Week controls

Dependent variable	1(Work)	
Other worker ill	0.089**	0.141***
	[0.036]	[0.052]
Other worker ill X Female		-0.095
		[0.069]
Mean Dependent Variable	0.807	0.807
Observations	3,951	3,951
R-squared	0.592	0.592

*Notes: Other worker ill = 1 if another household member reported missing work for a day in which s/he was planning to work and the reason for missing work was injury/illness. Sample includes respondents employed at baseline. All specifications include individual fixed effects and gender interacted with week of interview, enumeration area X week, and gender interacted with a control for the number of household members planning to work in that round. Standard errors in brackets, clustered at the household level: *** p<0.01, ** p<0.05, * p<0.1.*

Table A6: Effects of a Worker's Unexpected Illness on the Income of Other Household Members

Dependent variable	Income (cedis)				
Other worker ill	21.335	20.612	64.948	2.004	12.878
	[17.183]	[18.160]	[90.476]	[12.426]	[14.319]
Other worker ill X Female	-25.616	-17.848	-68.964	11.491	8.549
	[21.661]	[23.053]	[113.178]	[19.612]	[23.230]
HH Assets at Baseline X Other worker ill		-10.523			
		[20.826]			
HH Assets at Baseline X Other worker ill X Female		24.64			
		[24.411]			
HH Average Education X Other worker ill			-4.450		
			[8.736]		
HH Average Education X Other worker ill X Female			4.417		
			[11.583]		
Highest baseline earnings in household X Other worker ill				49.207	
				[40.071]	
Highest baseline earnings in household X Other worker ill X Female				-101.552**	
				[45.910]	
Highest usual hours of work in household X Other worker ill					24.664
					[46.347]
Highest usual hours of work in household X Other worker ill X Female					-89.162
					[53.808]
Mean dependent variable	3,948	3,766	3,948	3,948	3,948
Observations	116.4	113	116.4	116.4	116.4

*Notes: Other worker ill = 1 if another household member reported missing work for an entire week in which s/he was planning to work and the reason for missing work was injury/illness. Sample includes respondents employed at baseline. Assets are measured by the first principal component from an index of household assets including bed, wall clock, watch, player, radio, tv, sewing machine, fan, air conditioning, fridge, freezer, gas stove, shovel, landline telephone, cell, bike, motorbike, car, computer, livestock, farm implements, generator, land; then normalized to have mean zero and standard deviation one. Usual earnings and usual hours of work from reports in baseline survey. All specifications include individual fixed effects. Estimation uses least squares with trimming to account for censoring of the dependent variable (Honore, 1992). Regressions include controls for the number of household members planning to work in that round interacted with gender. Standard errors in brackets, clustered at the household level: *** p<0.01, ** p<0.05, * p<0.1.*

Table A7: Test for care-taking behavior

Panel A: Caretaking as an outcome

Sample	All respondents	Women only
Dependent variable	Hours on child care	1(Miss work due to caretaking)
Other worker ill	2.782	0.008
	[3.382]	[0.018]
Other worker ill X Female	2.784	
	[4.158]	
Mean dependent variable	6.555	0.020
Observations	3948	2207
R-squared		0.763

Panel B: Differential effects among respondents who engage in child care

Dependent variable	1(Work)	Days worked
Other worker ill	0.044	0.085
	[0.036]	[0.282]
Other worker ill X Female	-0.100	-0.308
	[0.070]	[0.403]
Any Child Care X Other worker ill	0.100	0.760*
	[0.070]	[0.435]
Any Child Care X Other worker ill X Femal	-0.079	-0.552
	[0.110]	[0.568]
Mean dependent variable	0.807	4.279
Observations	3,951	3,948
R-squared	0.507	

*Notes: Other worker ill = 1 if another household member reported missing work for an entire week in which s/he was planning to work and the reason for missing work was injury/illness. Column 3 of Panel A and column 1 of Panel B are estimated by OLS and columns 1 of Panel A and columns 2 and 3 of Panel B are estimated using least squares with trimming to account for censoring of the dependent variable (Honore, 1992). All specifications include individual fixed effects. Sample includes respondents employed at baseline. Regressions in column 1 of panel A and panel B include week-of-interview dummies interacted with gender and controls for the number of household members planning to work in that round interacted with gender. Standard errors in brackets, clustered at the household level: *** p<0.01, ** p<0.05, * p<0.1.*

Table A8: Effects of Worker's Own Future and Past Illness on Labor Supply

Dependent Variable	1(Work)	Days worked	Hours worked
Panel A: The worker him/herself ill next week			
Self ill next week	-0.014	-0.656	-6.483
	[0.110]	[0.678]	[5.718]
Self next week X Female	-0.048	0.047	3.294
	[0.132]	[0.902]	[7.434]
Other worker ill	0.114***	0.522*	5.180**
	[0.042]	[0.275]	[2.588]
Other worker ill X Female	-0.149***	-0.610	-6.251
	[0.055]	[0.390]	[4.060]
Mean dependent variable	0.806	4.274	37.61
Observations	3,514	3,514	3,514
R-squared	0.492		
Panel B: Self ill last week			
Self ill last week	-0.009	0.086	0.830
	[0.100]	[0.676]	[5.479]
Self ill last week X Female	-0.032	-0.326	-2.396
	[0.113]	[0.877]	[7.699]
Other worker ill	0.081*	0.402	5.043*
	[0.045]	[0.269]	[2.600]
Other worker ill X Female	-0.128**	-0.583	-6.739*
	[0.057]	[0.388]	[4.004]
Mean dependent variable	0.820	4.345	38.170
Observations	3,496	3,493	3,493
R-squared	0.529		

*Notes: Other worker ill = 1 in a given week if another household member reported missing work that entire week (if s/he was planning to work that week) and the reason for missing work was injury/illness. Self ill next week/previous week = 1 if that worker reported missing work that entire next week (if s/he was planning to work that week) and the reason for missing work was injury/illness. Sample includes respondents employed at baseline. Regressions include individual fixed effects and controls for the number of household members planning to work in that round interacted with gender. Column 1 is estimated by OLS and columns 2 and 3 are estimated using least squares with trimming to account for censoring of the dependent variable (Honore, 1992). Standard errors in brackets, clustered at the household level: *** p<0.01, ** p<0.05, * p<0.1.*

Table A9: Distribution of gender and high earner/hours status within household

		Male	Female	Total
Highest Baseline Earnings in Household				
No	Count	74	139	213
	Percent	38.7	58.2	49.5
Yes	Count	117	100	217
	Percent	61.3	41.8	50.5
Total		191	239	430
		100	100	100
Highest Usual Hours of Work in Household				
No	Count	79	124	203
	Percent	41.4	51.9	47.2
Yes	Count	112	115	227
	Percent	58.6	48.1	52.8
Total		191	239	430
		100	100	100
Highest Baseline Earnings in Household; Households with 2+ Workers Employed at Baseline only				
No	Count	74	137	211
	Percent	51.4	69.2	61.7
Yes	Count	70	61	131
	Percent	48.6	30.8	38.3
Total		144	198	342
		100	100	100
Highest Usual Hours of Work in Household; Households with 2+ Workers Employed at Baseline only				
No	Count	79	124	203
	Percent	54.9	62.6	59.4
Yes	Count	65	74	139
	Percent	45.1	37.4	40.6
Total		144	198	342
		100	100	100

Notes: Sample includes individuals employed at baseline.

Table A10: Week-to-week variation in wages

Dependent variable = Mean absolute within-person deviation in weekly hours worked

	Including weeks with zero hours		Conditional on any hours worked	
	Males	Females	Males	Females
Wage work, irregular payment	11.982	9.678	7.207	5.574
Wage work, regular payment	9.180	7.292	5.152	4.309
Self employed	10.331	8.870	6.597	6.833
P-value from F-test of difference in coefficients	0.496	0.473	0.321	0.005
Work close to home	9.792	8.224	5.854	6.249
Work far from home	7.758	5.756	7.251	6.729
P values from T-test of difference in coefficients	0.008	0.001	0.001	0.050

Notes: Sample includes respondents employed at baseline. P-values use standard errors clustered at the household level. Regular wage work is defined as jobs for which the respondent listed frequency of pay as every week, every two weeks, or every month; any other responses are characterized as irregular wage work.

Table A11: Heterogeneous Effects by Household Demographics

Dependent variable	1(Work)	Days worked	Hours worked	1(Work)	Days worked	Hours worked
Panel A: Working age adults						
Other worker ill	0.132	0.39	4.394	0.094	0.166	2.362
	[0.080]	[0.459]	[4.959]	[0.060]	[0.403]	[4.015]
Other worker ill X Female	-0.226	-0.28	-2.002	-0.147	-0.023	-0.667
	[0.142]	[0.661]	[6.875]	[0.100]	[0.550]	[5.432]
Number of Adults 18 to 64 in household	-0.007	-0.004	-0.066			
X Other worker ill	[0.010]	[0.051]	[0.529]			
Number of Adults 18 to 64 in household	0.014	-0.021	-0.371			
X Other worker ill X Female	[0.016]	[0.067]	[0.715]			
Number of Adults 18 to 64 out of LF in HH				-0.005	0.095	0.774
X Other worker ill				[0.026]	[0.150]	[1.293]
Number of Adults 18 to 64 out of LF in HH				0.009	-0.18	-1.818
X Other worker ill X Female				[0.036]	[0.179]	[1.676]
Net effect on Male 1 sd above mean	0.065	0.351	3.755	0.073	0.551	5.513
P-value	0.131	0.164	0.079	0.264	0.127	0.040
Net effect on Female 1 sd above mean	-0.030	-0.127	-1.832	-0.038	-0.206	-2.553
P-value	0.423	0.569	0.399	0.449	0.439	0.322
Mean dependent variable	0.807	4.279	37.660	0.807	4.279	37.660
Observations	3,786	3,783	3,783	3,786	3,783	3,783
R-squared	0.516			0.516		
Panel B: Older adults						
Other worker ill	0.093**	0.385*	4.008**	0.092**	0.381**	4.282**
	[0.038]	[0.259]	[2.332]	[0.036]	[0.240]	[2.232]
Other worker ill X Female	-0.138**	-0.463	-5.222*	-0.134**	-0.439	-4.972*
	[0.059]	[0.357]	[3.522]	[0.057]	[0.335]	[3.288]
Number of Adults 65+ in household	-0.085	-0.187	-0.624			
X Other worker ill	[0.057]	[0.429]	[5.277]			
Number of Adults 65+ in household	0.099	0.138	2.676			
X Other worker ill X Female	[0.066]	[0.764]	[9.499]			
Number of Adults 65+ in household out of				-0.143**	-0.326	-5.771**
labor market X Other worker ill				[0.065]	[0.541]	[10.325]
Number of Adults 65+ in household out of				0.137**	-0.173	-0.703
labor market X Other worker ill X Female				[0.060]	[1.077]	[20.743]
Net effect on Male 1 sd above mean	0.0421	0.273	3.633	0.0331	0.248	1.923
P-value	0.173	0.251357	0.265247	0.3	0.33267	0.663156

Net effect on Female 1 sd above mean	-0.0359	-0.107	0.0223	-0.0453	-0.262	-3.337
P-value	0.212	0.73571	0.995544	0.204	0.73571	0.995544
Mean dependent variable	0.807	4.279	37.660	0.807	4.279	37.660
Observations	3,786	3,783	3,783	3,786	3,783	3,783
R-squared	0.516			0.516		
Panel C: Children						
Other worker ill	0.061	0.211	3.494	-0.010	0.344	6.828
	[0.045]	[0.324]	[3.012]	[0.097]	[0.561]	[5.585]
Other worker ill X Female	-0.147**	-0.577	-7.910*	-0.034	-0.655	-9.037
	[0.069]	[0.467]	[4.613]	[0.109]	[0.675]	[6.798]
Number of children under 10 in household	0.024	0.154	0.44			
X Other worker ill	[0.031]	[0.208]	[1.854]			
Number of children under 10 in household	0.022	0.150	3.172			
X Other worker ill X Female	[0.037]	[0.323]	[2.612]			
Number of own children under 10				0.052	0.056	-1.270
X Other worker ill				[0.043]	[0.277]	[2.759]
Number of own children under 10				-0.033	0.206	3.032
X Other worker ill X Female				[0.042]	[0.329]	[3.143]
Net effect on Male 1 sd above mean	0.117	0.569	4.517	0.136	0.501	3.275
P-value	0.030	0.101	0.142	0.013	0.226	0.452
Net effect on Female 1 sd above mean	0.020	0.342	3.987	0.010	0.424	2.723
P-value	0.724	0.358	0.154	0.903	0.232	0.338
Mean dependent variable	0.807	4.279	37.660	0.807	4.279	37.660
Observations	3,786	3,783	3,783	2,724	2,722	2,722
R-squared	0.517			0.538		
Panel D: Marriage						
Other worker ill	0.034	0.020	2.373			
	[0.052]	[0.366]	[3.247]			
Other worker ill X Female	-0.08	-0.277	-5.078			
	[0.078]	[0.500]	[4.529]			
Other worker ill X Married	0.084	0.595	2.700			
	[0.071]	[0.462]	[4.663]			
Other worker ill X Married X Female	-0.074	-0.228	0.864			
	[0.102]	[0.661]	[5.987]			
Net effect on Married Male	0.118	0.615	5.073			
P-value	0.013	0.037	0.110			
Net effect on Married Female	-0.036	0.109	0.859			
P-value	0.570	0.732	0.748			

Mean dependent variable	0.807	4.279	37.660
Observations	3,803	3,800	3,800
R-squared	0.514		

*Notes: Other worker ill = 1 if another household member reported missing work for an entire week in which they were planning to work and the reason for missing work was injury/illness. Sample includes respondents employed at baseline. All specifications include individual fixed effects. Columns 1 and 4 are estimated by OLS and columns 2, 3, 5, and 6 are estimated using least squares with trimming to account for censoring of the dependent variable (Honore, 1992). Regressions include week-of-interview dummies interacted with gender, week-of interview dummies interacted with city, and controls for the number of household members planning to work in that round interacted with gender. Standard errors in brackets, clustered at the household level: *** p<0.01, ** p<0.05, * p<0.1.*

Table A12: Relationship between earnings and hours for self-employed

	Dependent variable = Earnings		
Hours	2.497***	2.289***	1.575***
	[0.547]	[0.404]	[0.202]
Winsorization	none	1st/99th	5th/95th
Mean dependent variable	115.9	104.6	83.25
Observations	2,389	2,389	2,389
R-squared	0.069	0.102	0.141

*Notes: Sample includes respondents self-employed at baseline. Estimation is via OLS. All specifications include individual fixed effects. Regressions include week-of-interview dummies interacted with gender, week-of interview dummies interacted with city, and controls for the number of household members planning to work in that round interacted with gender. Standard errors in brackets, clustered at the household level: *** p<0.01, ** p<0.05, * p<0.1.*

Table A13: Effects of a Worker's Unexpected Illness on the Labor Supply of Other Household Members, in Households in which a Female is Highest Earner at Baseline

Dependent Variable	1(Work)	Days Worked	Hours worked
Other worker ill	0.015	0.096	4.618
	[0.065]	[0.464]	[4.422]
Other worker ill X Female	-0.084	-0.420	-6.235
	[0.083]	[0.581]	[5.787]
Mean dependent variable	0.788	4.200	36.074
Observations	1,806	1,804	1,804
R-squared	0.536		

*Notes: Other worker ill = 1 if another household member reported missing work for an entire week in which s/he was planning to work and the reason for missing work was injury/illness. Sample includes respondents employed at baseline. All specifications include individual fixed effects. Column 1 is estimated by OLS and columns 2 and 3 are estimated using least squares with trimming to account for censoring of the dependent variable (Honore, 1992). Regressions include week-of-interview dummies interacted with gender, week-of interview dummies interacted with city, and controls for the number of household members planning to work in that round interacted with gender. Standard errors in brackets, clustered at the household level: *** p<0.01, ** p<0.05, * p<0.1.*

Online Appendix: Reasons for missing work Categorized as Illness/Injury

“MY DAUGHTER IS SICK"
”LOOKING AFTER HER GRANDMOTHER "
”LOOKING AFTER HER GRANDMOTHER"
”A Family member was sick"
”BECAUSE OF MY GRANDCHILDREN "
”BECAUSE OF THE CHILD "
”HER CHILD IS VERY SICK "
”HER MOTHER IS VERY SICK "
”HIS CHILD WAS SICK"
“HUSBAND WAS VERY SICK"
”LOOKING AFTER HER GRANDMOTHER "
”LOOKING AFTER HER GRANDMOTHER "
”LOOKING AFTER HER SICK MOTHER "
”LOOKING AFTER HER SICK MOTHER "
” MOTHER IS VERY SICK "
”MY CHILD WAS ILL"
”MY CHILD WAS SICK"
”MY DAUGHTER WAS SICK"
”NURSING A BABY"
”SHE IS TAKING CARE OF OF THE SICK MOTHE"
“SHE IS TAKING CARE OF SOMETHING "
”STILL TAKING CARE OF MY SICK DAUGHTER "
”STILL WITH MY SICK DAUGHTER "
”TAKING CARE OF CHILDREN "
”TAKING CARE OF HER NEWLY BORN BABY"
”TAKING CARE OF HER SICK MOTHER "
”TAKING CARE OF MY GRANDMOTHER "
”TAKING CARE OF MY SICK DAUGHTER "
”TAKING CARE OF SOMETHING "
”THE CHILD IS SICK "
”TOOK CARE OF MY SICK UNCLE"
”TOOK MY CHILD TO THE CLINIC"
”WAS TAKING CARE OF MY NEPHEW AT HOME"WAS TAKING CARE OF NEPHEW "
”a family member was sick"
”baby sitting"
”child was sick"
”my daughter was sick"
”my husband is sick"
”my kids are sick"
”my son was sick "
”my wife travelled so I hve to stay home"
”taking care of my sick sister"
”took my mom to the hospital "
”UNLESS MY TWIN CHILDREN START SCHOOLING"
”SHE IS TAKING CARE OF OF THE SICK MOTHER "
“MOTHER IS VERY SICK"
”LOOKING AFTER HER GRANDMOTHER "

”took care of my sick husband"
”MY DAUGHTER IS SICK"
”HAVE TRAVELLED TO TAKING CARE OF MY SICK DAUGHTER "
BECAUSE OF MY GRANDCHILDREN "
"BECAUSE OF THE CHILD "
"HER CHILD IS VERY SICK "
"HER MOTHER IS VERY SICK "
"HIS CHILD WAS SICK"
"LOOKING AFTER HER GRANDMOTHER "
"LOOKING AFTER HER SICK MOTHER "
"MOTHER IS VERY SICK "
"MY CHILD WAS SICK "
"MY DAUGHTER IS SICK"
"MY DAUGHTER WAS UNWELL"
"NURSING A NEWLY BORN "
"NURSING A NEWLY BORN BABY"
"TAKING CARE OF CHILDREN "
"TAKING CARE OF MY SICK DAUGHTER "
"WAS TAKING CARE OF MY NEPHEW "
"a family member was sick "
"baby sitting "
"my kids are sick"
"my son was sick "
"stayed home to care my sick husband"
"taking care of my sick sister"
"took care of my sick husband"
”HAVE TRAVELLED TO TAKING CARE OF MY SIC"
”STILL TAKING CARE OF MY SICK DAUGHTER "
”TAKING CARE OF MY SICK DAUGHTER "
“CARING FOR HER NEWLY BORN BABY" HELPING MY SISTER WHO JUST GAVE BIRTH" HELPING MY SISTER WHO JUST HAD A BABY " MOTHER WAS SICK AND I HAD TO TAKE HER T" MY DAUGHTER WAS SICK "
MY SISTER GAVE BIRTH SO I HAD TO HELP H"
Nursing a baby"
Nursing a baby "
Nursing a new baby"
TAKING CARE OF MY BABY"
TAKING CARE OF MY NEW BORN BABY AND SIC"
WAS ATTENDING TO HER DAUGHTER WHO HAS G"
child seriously ill and taking care of"
gave birth on the day of baseline inerv"
has put to birth "
my husband was sick"
nursing a baby"
nursing a baby "
nursing my newly born baby"
put to birth "

son is sick"
took my son to the hospital "
STILL TAKING CARE OF MY LITTLE BABY "
"I was sick"
"I was sick as a result of early pregnan"

Table O1: Table 3 Panel B with alternate measures of relative earnings/hours

Dependent variable	1(Work)	Days worked last week	Hours worked last week	1(Work)	Days worked last week	Hours worked last week
Panel A: Relative pay						
Other worker sick	0.039	0.095	1.46	-0.054	-0.363	-0.105
	[0.053]	[0.420]	[3.629]	[0.140]	[0.411]	[3.915]
Other worker sick X Female	-0.08	-0.102	-2.342	0.024	0.589	-5.38
	[0.077]	[0.513]	[4.719]	[0.223]	[1.545]	[11.690]
Above median baseline earnings in household	0.093	0.54	5.8			
X Other worker sick	[0.066]	[0.482]	[4.403]			
Above median baseline earnings in household	-0.097	-0.813	-6.112			
X Other worker sick X Female	[0.095]	[0.682]	[1.125]			
Relative baseline earnings in household				0.137	0.749	4.62
X Other worker sick				[0.122]	[0.621]	[5.633]
Relative baseline earnings in household				-0.148	-1.078	-0.042
X Other worker sick X Female				[0.213]	[1.462]	[11.074]
Observations	3951	3948	3948	3860	3857	3857
R-squared	0.507			0.507		
Panel B: Relative earnings potential within household						
Other worker sick	0.045	0.12	2.453	-0.01	-0.203	-1.246
	[0.055]	[0.272]	[2.105]	[0.119]	[0.670]	[5.978]
Other worker sick X Female	-0.11	-0.45	-3.561	-0.177	-0.766	-0.984
	[0.089]	[0.475]	[3.837]	[0.179]	[1.070]	[8.282]
Above median baseline usual hours of work	0.094	0.584	4.733			
in HH X Other worker sick	[0.063]	[0.380]	[4.034]			
Above median baseline usual hours of work	-0.036	-0.035	-4.419			
in HH X Other worker sick X Female	[0.120]	[0.631]	[5.757]			
Relative usual hours of work in HH at baseline				0.091	0.555	5.493
X Other worker sick				[0.102]	[0.594]	[6.141]
Relative usual hours of work in HH at baseline				0.058	0.308	-4.255
X Other worker sick X Female				[0.151]	[0.931]	[7.868]
Observations	3951	3948	3948	3951	3948	3948
R-squared	0.507			0.511		

*Notes: Other worker sick = 1 if another household member reported missing work for an entire week that she/he was planning to work that week and the reason for missing work was injury/illness. Sample includes respondents employed at baseline. Usual earnings and usual hours of work from reports in baseline survey. All specifications include individual fixed effects. Column 1 estimated by OLS and columns 2 and 3 least squares with trimming to account for censoring of the dependent variable (Honore, 1992). Regressions include week-of-interview dummies interacted with gender, city X week-of-interview dummies, and controls for the number of household members planning to work in that round interacted with gender. Standard errors in brackets, clustered at the household level: *** p<0.01, ** p<0.05, * p<0.1.*

Table O2: Point estimates corresponding to figure 2

Dependent variable	1(Work)	Days worked last week	Hours worked last week
Other worker sick X Choose 3.00/3.00	0.266***	1.499**	16.243**
	[0.060]	[0.614]	[7.361]
Other worker sick X Choose 2.70/5.70	0.054	0.434	2.580
	[0.076]	[0.379]	[4.064]
Other worker sick X Choose 2.40/7.20	-0.028	-0.593	-4.260
	[0.049]	[0.685]	[5.612]
Other worker sick X Choose 1.80/9.00	0.061	0.108	2.630
	[0.049]	[0.375]	[2.748]
Other worker sick X Choose 1.00/11.00	0.031	0.035	1.456
	[0.117]	[0.658]	[6.002]
Other worker sick X Choose 0/12.00	0.082	0.162	7.144
	[0.110]	[0.830]	[10.501]
Female X Other worker sick X Choose 3.00/3.00	0.109	0.588	1.529
	[0.083]	[0.869]	[10.133]
Female X Other worker sick X Choose 2.70/5.70	-0.045	0.218	3.390
	[0.077]	[0.660]	[7.599]
Female X Other worker sick X Choose 2.40/7.20	-0.095	-0.236	0.439
	[0.079]	[0.899]	[7.877]
Female X Other worker sick X Choose 1.80/9.00	-0.066	-0.398	-3.080
	[0.080]	[0.520]	[4.283]
Female X Other worker sick X Choose 1.00/11.00	-0.087	-0.597	-4.785
	[0.114]	[0.926]	[8.772]
Female X Other worker sick X Choose 0/12.00	-0.074	-0.124	-3.709
	[0.110]	[1.206]	[13.993]
Observations	3,951	3,948	3,948
R-squared	0.508		

*Notes: Other worker sick = 1 if another household member reported missing work for an entire week that she/he was planning to work that week and the reason for missing work was injury/illness. Sample includes respondents employed at baseline. All specifications include individual fixed effects. Column 1 estimated by OLS and columns 2 and 3 least squares with trimming to account for censoring of the dependent variable (Honore, 1992). Regressions include week-of-interview dummies interacted with gender city X week-of-interview dummies, and controls for the number of household members planning to work in that round interacted with gender.. Standard errors in brackets: *** p<0.01, ** p<0.05, * p<0.1.*

Table O3: Net Effects of the Illness of a Worker on Household-Level Labor Outcomes, using Winsorized Income measures

			Households with…			HH in which woman is highest earner at baseline
Sample of households	all	2 + earners at baseline	0 male earners at baseline	1+ male earner at baseline	2+ male earners at baseline	
Panel A: Winsorized at 1st/99th percentile						
Worker sick	-88.410***	-103.989***	-4.617	-95.371***	-137.590***	-3.546
	[24.418]	[39.034]	[20.507]	[26.954]	[47.327]	[18.661]
Worker sick X Female sick	28.856	61.79	-93.565**	68.664**	118.720**	-79.762**
	[30.776]	[40.455]	[44.968]	[30.359]	[55.901]	[32.739]
Observations	2,345	1,268	889	1,456	353	940
R-squared	0.62	0.631	0.639	0.601	0.564	0.59
Mean Dependent Variable	202.60	259.80	126.9	248.80	307.80	183.90
Panel A: Winsorized at 5th/95th percentile						
Worker sick	-85.421***	-100.121***	8.56	-90.377***	-130.919***	3.496
	[23.260]	[36.993]	[12.730]	[24.520]	[42.545]	[17.802]
Worker sick X Female sick	41.037	65.525*	-94.353***	78.114***	137.657***	-68.488**
	[27.202]	[38.809]	[28.243]	[27.485]	[47.645]	[27.735]
Overall effect of female sickness	-11.9609	18.8973	-30.5124	-11.8007	18.2577	-23.1955
P-value	0.5319	0.0976	0.0431	0.5164	0.0847	0.0206
Observations	2,345	1,268	889	1,456	353	940
R-squared	0.652	0.644	0.670	0.626	0.588	0.613
Mean Dependent Variable	202.60	259.80	126.9	248.80	307.80	183.90

*Notes: Worker sick = 1 if a household member reported missing work for an entire week in which s/he was planning to work that week and the reason for missing work was injury/illness. All specifications include household fixed effects, city X week-of-interview dummies, and controls for the number of household members planning to work in that round interacted with gender. Standard errors in brackets, clustered at the household level: *** p<0.01, ** p<0.05, * p<0.1.*

Table O4: Net Effects of the Illness of a Worker on Household-Level Labor Outcomes with EA x week controls

		Households with…			
Sample of households	all	2 + earners at baseline	1+ male earner at baseline	2+ male earners at baseline	HH in which woman is highest earner at baseline
Panel A: Dependent Variable = Total household income					
Worker ill	-89.583	-70.927	-110.175	-134.369***	-8.725
	[59.373]	[56.415]	[81.249]	[48.739]	[22.589]
Worker ill X Female ill	29.856	19.969	61.025	113.892*	-89.157*
	[61.731]	[57.564]	[81.457]	[59.902]	[46.729]
Observations	2345	1268	1456	353	940
R-squared	0.685	0.773	0.721	0.485	0.526
Mean dependent variable	202.60	259.80	248.80	307.80	183.90
Overall effect of female illness	-70.320	-44.240	-35.160	-20.480	-97.880
P-value	0.004	0.024	0.109	0.595	0.013
Expected male earnings loss from baseline	105.500	92.06	105.5	77.06	42.33
Fraction of expected loss compensated	0.224	0.116	0.387	-0.744	0.794
Expected female earnings loss from baseline	49.040	50.07	57.4	67.5	53.68
Fraction of expected loss compensated	-0.434	-0.0393	0.217	0.697	-0.824
Panel B: Dependent variable = Total Household Labor Hours					
Worker ill	-25.337***	-34.593***	-31.111***	-40.165***	-12.493
	[6.823]	[10.055]	[7.535]	[9.999]	[8.897]
Worker ill X Female ill	11.908	20.073*	19.385**	30.129**	-4.938
	[7.765]	[10.896]	[9.295]	[11.931]	[8.244]
Observations	2345	1268	1456	353	940
R-squared	0.859	0.862	0.876	0.709	0.809
Mean dependent variable	67.03	95.70	83.54	112.60	72.24
Overall effect of female illness	-16.490	-16.870	-15.470	-10.040	-17.430
P-value	0.000	0.000	0.004	0.178	0.001

*Notes: Worker ill = 1 if a household member reported missing work for an entire week in which s/he was planning to work that week and the reason for missing work was injury/illness. Expected earnings loss from baseline is calculated by taking the taking the average usual reported income from the baseline survey of individuals who are unexpectedly sick over the course of the survey. All specifications include household fixed effects, week of interview dummies interacted with enumeration area, and controls for the number of household members surveyed in that round. Standard errors in brackets, clustered at the household level: *** p<0.01, ** p<0.05, * p<0.1.*