Cancer Diagnoses’ Impacts on Family Incomes: Evidence from Canada

Sergei Filiasov, McMaster University, Hamilton, Ontario, filiasos@mcmaster.ca
Boris Kralj, McMaster University, Hamilton, Ontario
Arthur Sweetman, McMaster University, Hamilton, Ontario

Abstract: Focusing on individual and family income, and their components, we estimate average treatment effects for those with cancer diagnoses in Canada. Different (temporal) definitions of coupled and non-coupled households are employed to produce estimates by terciles of individual income. First, we find that the decrease in labour earnings is considerably but not fully mitigated by social insurance and non-labour income. Second, an added worker effect is observed for female partners of cancer survivors and a caregiver effect for male partners, but only in the second tercile of pre-diagnosis income of a cancer survivor. Also, the observed added-worker effect for wives originates from the upper two terciles of survival probabilities, while the caregiver effect for husbands originates from the lower two terciles. Finally, there are second-order effects of a cancer diagnosis due to the endogeneity of marital status (diagnosis-related marital formation/dissolution) and related selection issues. Although statistically significant, these effects do not affect our main findings qualitatively.

Keywords: added worker, caregiver, coupled households, cancer, family income, marital status

The views expressed in this paper are solely our own and do not represent the views of Statistics Canada or the Government of Canada.

JEL: I12, J12, J22
1. Introduction

Adverse health events affect different aspects of life and pose serious threats to financial stability. A vast body of literature reports large and negative effects of health shocks on labour market outcomes of affected individuals (e.g., Pedron et al., 2019; Shahrbanian et al., 2013; de Boer et al., 2009). Hence, understanding how different insurance mechanisms work and through what channels is of paramount importance. In this study, we focus on the role of marital status, including same-sex couples, in the effects of health shocks on income and its components including social insurance (transfers, taxes) and non-labour income. We also focus on the heterogeneity of effects across the income distribution.

In general, the overall effect on labour market outcomes of spouses, and, hence, coupled families, is ambiguous in theory (Jeon & Pohl, 2017; Garcia-Gomez et al., 2013). Two main forces could be at play. The so-called added worker effect (e.g., Lundberg, 1985) results in the increase of labour market participation of (directly) unaffected spouses to compensate for the negative income effect. On the other hand, it could be the case that a family member affected by a chronic disease needs additional care or lost household production requires to decrease labour supply. In addition, health shocks can also affect the wife’s behaviour by changing her reservation wage (Siegel, 2006). There is mixed evidence in the literature depending on the country, local healthcare and social insurance systems, age, and education (e.g., Garcia-Gomez et al., 2013; Datta Gupta et al., 2015; Persson et al., 2020).

Most of the literature focuses on labour market participation and income, family income, or social insurance receipt. The literature largely ignores the possible heterogeneity of intra-household substitution across the income distribution and income components. In this study, we attempt to fill this gap by utilizing three linked Canadian datasets: administrative income tax records, the Cancer registry and the Canadian Community Health Survey.

We use a novel matching methodology proposed by Fadlon & Nielsen (2021) to address the endogeneity of health shocks born by the differences in ex-ante expectations about future health. Specifically, we match individuals diagnosed with cancer to similar individuals but with diagnosis five years later. Using the matched sample, we estimate a two-way fixed-effects model for various income components separately for people based their marital/couple status. We use two definitions of being coupled: based on a 10-year period around cancer diagnosis and based
only on one year before the diagnosis. First, we estimate that, for a cancer diagnosis, the average treatment effect on the treated with respect to labour income is a reduction of about $3,200 to $7,200 (in 2019 Canadian dollars). Second, we find that the decrease in labour earnings is considerably but not fully mitigated by social insurance for both genders, and by non-labour income for the diagnosed non-coupled males.

Third, the family income of coupled diagnosed males seems to be better insured than the family income of non-coupled males in the second tercile of income distribution. This is primarily driven by the increase in income of unaffected members of the couple family of diagnosed males who are in the middle of the pre-diagnosis individual total income distribution. The result is consistent with the added worker effect for the healthy female partners. The reverse is true for diagnosed coupled females in the second tercile of income distribution which is consistent with the caregiver effect for their male partners. The findings also imply that the observed added-worker effect for wives is originating from the last two terciles of survival probabilities, while the caregiver effect for husbands is originating from the first two terciles. Furthermore, we show that there exist second-order effects of a cancer diagnosis. In particular, we show that the marital status is endogenous, with a positive effect on coupled status for previously non-coupled males, and a negative one for previously non-coupled females. Finally, using two alternative sample stratification by marital status, we demonstrate that switchers substantially differ from the other two groups in observed characteristics, but this does not affect our main results qualitatively.

The paper proceeds as follows. Section 2 presents a brief literature review. Sections 3 and 4 describe the data, sample, and methodology. Section 5 discusses our main findings, and section 6 concludes.

2. Literature review

Negative health shocks affect different aspects of life through various mechanisms depending on the socio-economic status of the person and the external environment in which they live that influences their behavioural responses. There is a substantial literature on the overall effects of health shocks, such as non-infectious chronic diseases that usually persist for long periods of time, on labour market outcomes (see systematic reviews by Pedron et al., 2019; Shahrbanian et al., 2013; de Boer et al., 2009). However, the effects on spousal and family labour market outcomes have been given less attention. In the next section, we briefly review the available
evidence in the literature on effects on total household income and its main component – labour market earnings, and on mechanisms such as intra-household supply substitution affecting spousal labour supply. Later we move to the discussion of the heterogeneity of effects across income components and income distribution.

2.1. Health Shocks and Labour Market Outcomes of Spouses and Families

The available literature that studies how spouses or partners (we will use these terms interchangeably), or, less often, households adjust their labour supply in response to a health shock considers a vast range of chronic diseases. In general, it is argued that the overall effect on labour market outcomes of spouses is ambiguous in theory (Jeon & Pohl, 2017; Garcia-Gomez et al., 2013). Two main forces could be at play. The so-called added worker effect (e.g., Lundberg, 1985) manifests in an increase of labour market participation by (directly) unaffected spouses to compensate for the negative income effect. On the other hand, a family member directly affected by a chronic disease may need additional care or may decrease their contribution to household production, requiring the partner to decrease labour supply. There is mixed evidence in the literature depending on the country, local healthcare and social insurance systems.

Furthermore, Siegel (2006) suggests that although the husband’s health conditions may influence the wife’s behaviour through income effects, it can also affect the wife’s behaviour through changing her reservation wage. Thus, he argues that to estimate the wife’s preference attitudes over providing care for her husband by herself or through formal care, one should control for the husband’s income which, in turn, could be endogenous. Therefore, Siegel uses labour demand shifters to instrument for the husband’s earnings. When considering eight chronic diseases, Siegel finds that only heart problems increase the probability of a wife’s labour participation in the US. In addition, Berger & Fleisher (1984) indicate that the generosity of transfers plays an important role in the wife’s decision to increase labour supply following the deterioration of her husband’s health since these transfers help to compensate for lost income. It is worth noting that these considerations are rarely simultaneously accounted for in the empirical literature reviewed below.

2.1.1. Evidence from Developed Countries
Additional evidence for the US comes from Dalton & LaFave (2017). Using the Panel Study of Income Dynamics from 1999-2011, they show that non-healthcare consumption of unmarried households falls following worsening health triggered by different conditions including chronic ones. On the contrary, married households manage to mitigate those shocks.

There is also heterogenous evidence for several European countries. For example, Garcia-Gomez et al. (2013) apply matching and difference-in-difference estimators to Dutch data. As a part of their analysis, they find that spousal participation and earnings drop following the occurrence of disability. The effects are higher and especially pronounced for male spouses. Further, Mussida & Sciulli (2019) investigate the issue using data from Italy, France, and the UK. The authors use a dynamic probit model that accounts for heterogeneity and endogeneity of initial conditions. The findings indicate that, if formal caregiving costs for wives are relatively low (which is the case in the UK and France as compared to Italy), then a wife increases labour supply in response to the disability of a husband. Persson et al. (2020) use Swedish data from 2005 to 2016 and show that stroke is negatively associated with spouses’ employment (for both genders) which is especially pronounced at lower age and education levels. On the contrary, Braakmann (2014) finds no support of the effect of spousal disability (broadly determined by German law) on the labour supply on intensive and extensive margins of the other partner (both sexes) in Germany in 1984-2006. The author also reports no effects of spousal disability on wages. On the other hand, there is strong evidence that individuals decrease labour supply in response to their own disability. However, these results are conditional on strong assumptions since the study does not deal with the endogeneity in any way except by including various controls. Fadlon & Nielsen (2021) estimate the elasticity of labour market participation with respect to social benefits around -0.26 for Denmark. This suggests that formal social insurance is a substitute for informal insurance. They find that non-fatal shocks do not affect spousal labour supply (due to adequate social insurance coverage) while fatal events considerably increase the labour supply of surviving spouses. In addition, Bernasconi et al. (2022) confirm the added worker effect when facing a stricter and less generous disability benefit regime for both men and women in the Netherlands but only for partners of sick individuals with a temporary work contract.

Finally, applying matching estimators to Japanese data Niu (2016) shows that there are no significant effects on hours worked by family members where the relative is diagnosed with mental
illness. The author suggests that this could be related to different social and cultural settings in Japan as opposed to the US and the UK.

2.1.2. Evidence from Canada

Humphries et al. (2020) provide descriptive evidence from Quebec, Canada that indicates the existence of various asymmetries in wage losses of husbands whose spouses were diagnosed with nonmetastatic breast cancer. In particular, self-employment and distance to the hospital are associated with higher losses. Jeon & Pohl (2017) provide additional evidence for Canada using administrative data. Examining cancer diagnoses, they employ propensity score matching coupled with a difference-in-difference estimator to provide nationally representative estimates of the effects of this chronic disease. They find that spousal labour supply falls in response to the diagnosis which can be interpreted as the provision of care to the partner. Later, Jeon et al. (2020) investigate the effects of acute myocardial infarction, stroke, and cardiac arrest in Canada. In contrast to the previous results on cancer, the authors do not find any significant effects on spousal labour supply except for the case of severe strokes.

2.1.3. Evidence from Developing Countries

Acuna et al. (2019) investigate the added worker effect in Chile using such health shocks as arthritis, asthma, and hypertension. They argue that these are unanticipated health shocks that are not likely to be correlated with labour supply or work preferences (and are also determined by genetic factors among others). They find empirical evidence of the added worker effect for arthritis but not for asthma and hypertension. In addition, they suggest that the effects are heterogeneous over the lifecycle and are the largest in the case when a husband is diagnosed with arthritis relatively early in life.

In China, Dong et al. (2020) investigate the effects of the presence of a family member suffering from senile chronic diseases on workforce participation. The authors use propensity score matching to deal with potential endogeneity. Their findings support the added worker effect – the income effect seems to be partially offset by the increased labour supply of the family members. In contrast, using Chinese data Shen et al. (2019) show that spousal working hours decrease after a diabetes diagnosis. The result holds for both women and men but is insignificant for families with higher socioeconomic status.
2.2. Open Questions in Intra-household Substitution: Income Composition and Distribution, and Endogeneity of Marital Status

The literature on the income and labour market effects of interactions between health shocks and different types of insurance, including income insurance, is less numerous and less geographically diverse. It largely ignores the possible heterogeneity of intra-household substitution across the income distribution and income components. Lastly, the marital status (or partnership) can be endogenous itself, which can also have second-order effects on family income.

First, the effects could be very different across different formal social insurance systems. This would largely depend on two components of social insurance: health insurance and income insurance. In systems with a dominant private health insurance sector, having a working spouse with available health insurance plays an additional important role. An analysis of survey data from the US suggests that employer-provided insurance and paid sick leaves are strongly positively associated with job retention following a colorectal cancer diagnosis (Veenstra et al., 2018). More credible evidence is provided by Bradley et al. (2013). Using a quasi-experimental design, the authors find that women who rely on their employer-provided insurance (i.e., do not have access to their partner insurance) reduce their labour supply by a smaller amount. This is also consistent with Bradley et al. (2007). Bradley et al. (2012) investigate this issue for men and find similar results. In particular, men are found to be more likely to continue working after a health shock if the associated future costs are high irrespective of increased morbidity.

On the other hand, with universal health insurance, being coupled does not provide the above benefit and plays a role primarily through the intra-household substitution and income insurance. However, most researchers either focus on labour income, total income, or family income. They do not consider different components of income other than social insurance transfers. Moreover, to our knowledge, no study focuses on the heterogeneity and roles of intra-household substitution across the income distribution, which is one of the most important heterogeneity dimensions relevant for the design of social policies. Some researchers consider the interactions between social insurance and informal insurance but do not conduct the heterogeneity analysis across income distribution (e.g., Fadlon & Nielsen, 2021). Others provide estimates of the effects of health shocks on spousal labour market outcomes for different education levels but not
income levels directly (e.g., Persson et al., 2020). In our study we attempt to fill this gap by utilizing a subset of administrative data for Canadian cancer survivors.

In addition, almost all existing literature effectively assumes exogeneity of the marital status. A common practice is to specify a cohort of always married individuals within a pre-specified period of time around a health shock. This, however, ignores two important issues: endogeneity of marital status and selection. Recent evidence from Germany shows that mental but not physical health shocks lead to a higher probability of breakup (Bunnings et al., 2021). Ehlert (2021) also demonstrates that the probability of marriage for previously unmarried couples increases after severe health shocks, which is driven by (anticipation of) financial incentives such as receiving survivor benefits. The second issue is potential selection (which we demonstrate later). Selecting always married households over a long period of time can potentially mean selecting a very different group of people since success in marriage markets has been shown to be related to success in labour markets (e.g., Kambourov et al., 2015; Calvo et al., 2021). It could also induce selection on observables, such as age, or unobservables.

3. Data and Sample

For our analysis, we use de-identified records from the Canadian Community Health Survey (CCHS) – All Annual cycles (2000 - 2017) linked to the International Agency for Research on Cancer (IARC) incidence TMF dataset (1992-2016) and the T1 Family File (T1FF; 1993-2017).1 The datasets are provided by Statistics Canada through the Research Data Centers.2,3 We define the treated group as all individuals who were diagnosed with some kind of cancer during the observation period. We only consider the first occurrence observed in the data. The algorithm used to eliminate duplicate tumours from IARC TMF can be found in Table A.1 in the appendix. In addition, treated individuals are restricted to ages 25 to 55 in order to focus only on potential labour market participants within the observation period. We focus only on cancer survivors since the spousal and family tax data is not available if the person is deceased. For our analysis, we use five calendar years before the shock, the year of the shock, and four years after the shock.

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1 Cancer data for residents of Quebec are not available after 2010.
3 Note that the counts are rounded to base 10 and dollar amounts to base $100 (or $10 if amount is below $1,000) as per Statistics Canada project specific rules in compliance with the Statistics Act.
In order to decompose total individual income into different components, we use the following definitions of its components (given the available data). We define labour income as the sum of employment earnings, self-employment income, and other income. Non-labour income is defined as the sum of limited partnership income, dividends, interest and other investment income, net rental income, alimony or separation allowances, other income, pension, and superannuation income. Transfers (including refundable credits) equal to the sum of old age security pension, income received from Canada/Quebec pension plan, net federal supplements, employment insurance, goods and services tax credit, provincial refundable tax credits, social assistance, workers’ compensation, child tax benefit, family benefits, universal childcare benefit, registered disability saving plan, and working income tax credit. Taxes include federal taxes, provincial taxes, and Quebec abatement.

Although, some variables relevant for several components are not present in the data (e.g., exempt employment income for Status Indians as defined by CRA; refundable medical expenses), our variables are able to explain more than 99.5% of the variation in the total individual income of the treated group as defined in the T1 Family File. Moreover, since we do not have income data on partners of affected individuals, we use total family income (sum of individual total incomes) and after-tax family income. In addition, the scaled versions of the family income variables (divided by the square root of family size) are also used in the analysis to account for the economy of scale effect. Total family income is only available starting from the 1997 tax year while after-tax income and family size are only available after 1999. We focus on the sample with pre-tax family income available.

All income variables are inflated to 2019 prices using the Canadian Consumer Price Index (CPI). In addition, we top- and bottom-code these variables at the 1st and 99th percentiles, respectively, to mitigate the influence of outliers and erroneous data. In the later analysis, we also use income variables relative to the average pre-treatment individual or family income. These variables are top- and bottom-coded at 5th and 95th percentiles due to extremely long tails of the distributions.

Since the administrative data is linked to the CCHS survey data, we also make use of the sample weights and produce two versions of the same output. Since the CCHS is not a panel, the sample weights are cross-sectional. Therefore, these weights make our sample representative of
people in each cycle of the CCHS used, conditional on our sample selection criteria described above. Effectively, the weights would not matter in case of, for instance, homogeneity of the effects across individuals. In the case of heterogeneity of the effects, the two versions of the output will differ to some extent. In our analysis, the weights are normalized within each analyzed group to produce the total number of individuals equal to the unweighted total unless otherwise stated. We do not adjust weights for having a tax record since it may reflect a person’s death or migration, the former being more likely given our context. Hence, we perform our analysis conditional on surviving, staying in Canada, and filing taxes.

In addition, we merge publicly available Statistics Canada age-specific five-year net survival estimates for primary sites of cancer, by sex. These estimates are reported for 56 different cancer groupings which are based on topography and ICD-O (v3) histology classifications. We use the estimates for people diagnosed with cancer in 2006-2008 (or in 2007-2010 if data are missing for 2006-2008). Based on these estimates, we construct terciles of survival probabilities.

Finally, to explore the endogeneity of partnership status, we use two definitions of being coupled. In one of the definitions, an individual is defined as coupled if he/she is reported married or is in a common-law partnership in the year prior to the year of the shock, according to the T1 Family File. This definition tries to address some of the selection issues mentioned above. However, the total impact on family income under this definition consists of two effects: an effect on the income itself as well as an effect on partnership status, and subsequent change in income due to this change. Under the other definition, we define three groups of individuals: always coupled during ten years around a cancer diagnosis; never coupled; and switchers, i.e., individuals who switch their status at least once during the ten years (23 and 24% of the sample of males and females respectively). The last two groups are usually excluded from the analysis in the existing literature. We, however, are specifically interested in the switchers, and in how results depend on including and excluding this group from the analysis.

4. **Methodology**

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We use the matching procedure described in Fadlon & Nielsen (2021). In their study, the authors show that unaffected and affected by a health shock Danish households have very different pre-treatment trends in outcomes even when matched on observables. They suggest that the problem is primarily caused by differences in ex-ante expectations about future health. They propose matching affected households to those that experience the same health shock in the (short-term) future, i.e., the timing of the shock is assumed to be quasi-random within a relatively short period of time. Our study uses this method combined with conventional difference-in-difference to estimate the average treatment effects on the treated.

Following Fadlon & Nielsen (2021), we match affected individuals in year $t$ to affected individuals in year $t + 5$ who are aged 30 to 60 in the year of the shock. This allows us to look at the average effect over 4 years after the year of the first observed cancer diagnosis. We assign a pseudo diagnosis event at time $t$ to the control group. Therefore, our treatment group includes people diagnosed in 2002 – 2011, and control (defined later) includes people diagnosed in 2007 – 2016. We further center the time to the diagnosis for each year-specific treatment cohort around the diagnosis year, and each control cohort around the pseudo diagnosis year. Note that both treated and control units are the same age at each value of the “time to diagnosis” variable.

The proportion of women diagnosed with cancer among all diagnosed is presented in Figure A.1 in the appendix. The weighted and unweighted proportions of females diagnosed with cancer among all diagnosed conditional on age at diagnoses are depicted in Figure A.2 in the appendix. Notably, there are more females than males who are diagnosed with cancer, especially around the age of 40. Finally, Appendix Figure A.3 presents the proportions of coupled people in the year of diagnosis. The last figure indicates that weighted and unweighted descriptive statistics differ substantially. Moreover, the weighted versions of statistics tend to be more volatile which is to be expected.

To estimate average treatment effects on the treated we use the following regression:

$$ y_{it} = \alpha_i + \theta_t + \beta_1 post_{it} + \gamma post_{it} \cdot treated_i + \epsilon_{it}, \tag{1} $$

where $y_{it}$ is a dependent variable (e.g., a specific income component); $\alpha_i$ is a unit-specific fixed effect; $\theta_t$ is a tax-year-specific fixed effect; $post_{it}$ is an indicator of post-treatment periods (periods from 0 to 4); $treated_i$ is equal to one for the treated group and zero for the control group.
We estimate the regressions separately for males and females as well as for coupled and non-coupled individuals/families under two separate definitions described above. We do it by fully interacting the right-hand side of the regression with both gender and coupled indicator variables.

In addition, for some specifications, we also estimate the heterogenous effects across tercile of the adjusted total individual or family income. The adjusted total individual income is a residual from a fully nonparametric regression of total individual income on gender and tax year, run on all pre-treatment periods. For the adjusted family income, we also include family size in this regression. This is done to normalize the income distribution before splitting the sample into income terciles. Finally, we also present results by the severity of cancer using the terciles of survival probabilities for each of 56 groupings (as described earlier).

As our main dependent variables, we either use the income components in levels or ratios relative to the pre-treatment average total individual income. The latter approach would be equivalent to dividing point estimates from regression in levels by the average value of income within each group only if the effects are homogenous across individuals.

The standard errors are obtained by bootstrapping. We use bootstrap replicate weights provided by Statistics Canada. We perform 499 bootstrap replications for each regression.

5. Results

5.1 Always/never coupled

In this sub-section, we discuss implications of a definition of couple families that is more common in the literature—those that are always coupled during the observation window. Here we define three groups: always coupled during all ten years; never coupled; switchers, i.e., people who change marital status at least once during the ten-year period.

First, we provide raw averages of income components for always coupled, never coupled, and switching individuals by their gender. These graphs for selected income components are presented in Figure 1 and Figure 2. All other graphs can be found in Figure A.4 in the Appendix. The analogous graphs for switchers are presented in Figure A.5 in the appendix. For most of the income components, the assumption of parallel trends appears to hold. This is a noteworthy result given that we perform exact matching using only the timing of the shock for people in a wide age
interval. In addition, note that weighted averages are expected to be more volatile than unweighted ones.

![Graphs showing income components](image)

**Figure 1.** Averages of selected income components.

From Figure 1 we can see that the total individual income of coupled males is higher than that of non-coupled. The reverse is true for females. This is consistent with the intra-household distribution of labour and non-labour related activities between the two genders. Furthermore, the family income of diagnosed coupled males seems to recover faster than the income of diagnosed coupled females. In addition, Figure 2 shows the evolution of individual transfers. There is an
apparent increase for coupled and uncoupled individuals for both genders. This increase is larger for non-coupled than coupled females. However, looking at graphs may in part be misleading since we do not adjust, for instance, for time-fixed effects (e.g., growth in real wages). Hence, we proceed to the results from estimating equation (1), which are presented in Table 1.

![Figure 2. Averages of individual transfers.](image)

There are a few notable issues in Table 1. First, the estimated average treatment effect on the treated of a cancer diagnosis for labour income is a decline of between about $5,900 to $3,300 for both females and males, while being lower (in absolute value) for never coupled females and higher for always coupled males. For the switchers, the estimates are similar.

This negative effect on labour income gets only partly mitigated by an increase in non-labour income and transfers, resulting in estimated declines in the total individual income of around $4,800 to $800. The change in the average non-labour income is the highest and statistically significant at the 10% level for males with switching marital status. For never-coupled females, this estimate is also positive and large but not statistically significant at the 10% level (statistically significant only at the 15% level). This indicates that non-labour income serves as a self-insurance mechanism for a selected group of males, and perhaps females. In addition, both males and females with changing marital status have the highest increase in transfers.

Another result is the decrease in taxes. Although this result is not surprising and has a “technical” nature, it still shows that a sizable part of the decrease in pre-tax income is mitigated by the tax system. The result is consistent across different groups and is comparable to the increase in transfers.
Table 1. Average treatment effects on the treated on individual income components, regressions in levels.

<table>
<thead>
<tr>
<th></th>
<th>Total Income</th>
<th>Labour Income</th>
<th>Non-Labour Income</th>
<th>Transfers</th>
<th>Taxes</th>
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<tbody>
<tr>
<td><strong>Male</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Never coupled</td>
<td>-3688.0*</td>
<td>-5872.4***</td>
<td>683.2</td>
<td>887.6***</td>
<td>-882.8</td>
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<tr>
<td></td>
<td>(2013.0)</td>
<td>(2067.7)</td>
<td>(626.2)</td>
<td>(330.0)</td>
<td>(693.8)</td>
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<tr>
<td>Always coupled</td>
<td>-3233.3*</td>
<td>-3784.1**</td>
<td>-107.3</td>
<td>822.0***</td>
<td>-1142.5*</td>
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<td></td>
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<td>(1796.2)</td>
<td>(919.6)</td>
<td>(195.2)</td>
<td>(671.8)</td>
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<td>Switching status</td>
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<td>1462.6*</td>
<td>1022.7**</td>
<td>-1183.4^</td>
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<td>(2371.7)</td>
<td>(859.8)</td>
<td>(402.8)</td>
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</tr>
<tr>
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<td>-3342.6^</td>
<td>1098.5^</td>
<td>674.1**</td>
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<td>(2250.8)</td>
<td>(755.3)</td>
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<td>331.4</td>
<td>526.1***</td>
<td>-817.8***</td>
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<td>(349.0)</td>
<td>(288.4)</td>
<td>(256.5)</td>
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</table>

Standard errors in parentheses. Standard errors are bootstrapped using 499 replications and CCHS replicate weights provided by Statistics Canada.

^ p<0.15, * p<0.1, ** p<0.05, *** p<0.01
Table 2. Average treatment effects on the treated on family income, regressions in levels.

<table>
<thead>
<tr>
<th></th>
<th>Male</th>
<th></th>
<th>Female</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Family Income</td>
<td>Scaled Family Income</td>
<td>Scaled After-Tax Family Income</td>
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<td>-3095.9</td>
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<td>-3795.5^</td>
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<tr>
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<td>(2470.6)</td>
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<tr>
<td>Always coupled</td>
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<td>905.6</td>
<td>1116.7</td>
</tr>
<tr>
<td></td>
<td>(2583.7)</td>
<td>(1675.7)</td>
<td>(1185.5)</td>
</tr>
<tr>
<td>Switching status</td>
<td>-2167.7</td>
<td>-897.4</td>
<td>184.8</td>
</tr>
<tr>
<td></td>
<td>(4257.5)</td>
<td>(3047.7)</td>
<td>(2341.2)</td>
</tr>
<tr>
<td>N</td>
<td>68160</td>
<td>61470</td>
<td>61470</td>
</tr>
<tr>
<td>N groups</td>
<td>7430</td>
<td>6690</td>
<td>6690</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Female</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Never coupled</td>
<td>-1726.1</td>
<td>-191.4</td>
<td>-461.1</td>
</tr>
<tr>
<td></td>
<td>(2901.4)</td>
<td>(2355.4)</td>
<td>(1665.3)</td>
</tr>
<tr>
<td>Always coupled</td>
<td>-4616.1**</td>
<td>-3537.6***</td>
<td>-2325.8***</td>
</tr>
<tr>
<td></td>
<td>(2053.8)</td>
<td>(1216.9)</td>
<td>(889.4)</td>
</tr>
<tr>
<td>Switching status</td>
<td>-8580.5***</td>
<td>-5173.6***</td>
<td>-3888.1***</td>
</tr>
<tr>
<td></td>
<td>(2548.8)</td>
<td>(1759.4)</td>
<td>(1326.7)</td>
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<td>N</td>
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<td>97690</td>
</tr>
<tr>
<td>N groups</td>
<td>11770</td>
<td>10300</td>
<td>10300</td>
</tr>
</tbody>
</table>

Standard errors in parentheses. Standard errors are bootstrapped using 499 replications and CCHS replicate weights provided by Statistics Canada.

^ p<0.15, * p<0.1, ** p<0.05, *** p<0.01
Moving to the effects on family income, from Table 2 we can see that there is a consistent difference between family incomes for always coupled and never coupled males. This might indicate that the income of a healthy female partner increases, perhaps, following the labour supply increase. This difference is even more pronounced for scaled family incomes and is statistically significant at the 10% level for males (p-values not reported). The estimated effect on the difference between family and individual incomes is around $2,600 and is statistically significant at the 10% level. This is not true, however, for women diagnosed with cancer. Indeed, the estimates for always coupled females seem to be negative higher in absolute value than for never coupled females, suggesting consistent with the absence of added worker effects or even the presence of caregiver effects in some sub-populations. The estimate for family income of never-coupled females is statistically different from the estimates for the other two groups at least at 10% level (p-values not reported in the table). Finally, note that the estimated effects for female switchers seem to be larger in magnitude. These results might include the change in family income due to endogenous changes in marital status in the treatment group. We investigate this issue later.

![Figure 3](image)

*Note:* standard errors are bootstrapped using 499 replications. Range spikes represent 90% CIs. “F” stands for “Females”, while “M” stands for “Males”.

*Figure 3.* Estimated effects on individual total income by income terciles.
Next, we consider the heterogeneity of the effects across terciles of individual total income. In addition, we present results for relative income, where we normalize the dependent variable by the average value of total adjusted income prior to the diagnosis (as described earlier). The results are depicted in Figure 3.

Figure 3 reveals that the estimated effects, although heterogeneous, are still negative for almost all groups. The differences between coefficients are not statistically significant at any reasonable level (p-values are not reported). Furthermore, Appendix Figure A.6 depicts the estimated effect on total individual income by terciles of survival probabilities. Although the differences in estimates are not statistically significant, the largest negative effects are observed at the lowest terciles of survival probabilities for always coupled and switching females, and for never coupled and switching males. The relationship of estimates coefficients with respect to survival terciles seems to be reversed for two genders for always and never coupled individuals, while it seems to be the same for switching individuals. The results for relative changes in transfers and taxes can be found in Figure A.9 in the appendix.

![Total Family Minus Total Individual Income](image1)

**Note:** Standard errors are bootstrapped using 499 replications. Range spikes represent 90% CIs. “F” stands for “Females”, while “M” stands for “Males”.

**Figure 4.** Estimated effects on the difference between family and individual total incomes by income terciles.

Figure 4 addresses the effects of the cancer diagnosis on the difference between family and individual total incomes, where total income reflects all other individuals in a census family and
not only partners. However, the estimates are still reflective of the influence of having a partner one year before diagnosis on family income. The results for individuals with changing marital status are presented in Figure A.7 in the appendix.

First, we can see that the estimated effect on the income of family members other than the affected person is around $3,600 in the second tercile of the income distribution in the specification in levels for always coupled males. It is statistically significant at the 1% level. In the specifications with relative income changes, it is still positive (around 6%) but at the margin of statistical significance. This seems to be reversed for coupled females with both coefficients being large in absolute value than for males and being significant at least at 5% level. The results are consistent with the added worker effect for healthy wives and the caregiver effect for healthy husbands in the middle of the income distribution. This suggests that the overall results in Table 2 are driven by individuals from the middle class, which could be of particular interest to policymakers.

Appendix Figure A.7 reports results for people with switching status. Although most estimates are not statistically significant, the signs of the coefficients for the two lower terciles are consistent with the findings for the middle of income distribution above. Moreover, the results for male switchers are mirror-symmetric of the results for female switchers. Note again that these coefficients reflect the effects on spousal income as well as the effects on family formation (relative to the control group).

Furthermore, we report the effects on the difference between family and individual total incomes by terciles of survival probabilities in Figure A.8 in the appendix. Although most of the estimates are not statistically significant, the results do imply that the observed (for people in the middle of the income distribution) added-worker effect for (healthy) wives is originating from the last two terciles of survival probabilities (moderate and least severe cancers), while the caregiver effect for (healthy) husbands is originating from the first two terciles (moderate and most severe cancers).

So far, we have seen those effects of a cancer diagnosis on people with switching marital status are only partially reflective of the effects on always or never coupled individuals. This could
be due to the second-order effects such as endogeneity of marital status or it could be related to the selection issues, i.e., switchers could be an entirely different sub-population group.

![Distribution of age at diagnosis by marital status during 10-year window.](image)

*Figure 5. Distribution of age at diagnosis by marital status during 10-year window.*

Figure 5 shows the distribution of age at diagnosis by coupled status during a 10-year window using our definition above. It illustrates the selection problem that stems from the stratification of the sample by marital status. While the always coupled and never coupled groups of people seem to be quite similar in terms of age distribution, the switchers appear to be much younger. This means that if switchers (which comprise almost 25% of our sample) are excluded from the analysis, this would lead to a very selected sample and unrepresentative estimates of the role of intra-household substitution. Moreover, these substantial differences in single observable characteristics imply that there might be other, including unobservable, differences.

In addition, Table 3 illustrates the endogeneity of marital status. In particular, the probability of being coupled is, on average, 5.7% higher (compared to the controls) among all diagnosed males in the first tercile of the income distribution. This effect is statistically significant at the 5% level. The estimate for female switchers is around -2.7% in the middle of the income distribution. Note that the effects from the appearance of new tax filer in the family only enter the estimates for switchers while the estimates for always/never coupled individuals are not contaminated by this.
Table 3. Estimated effects on being coupled (measured as 0 or 1) after diagnosis.

<table>
<thead>
<tr>
<th></th>
<th>Male</th>
<th>Female</th>
</tr>
</thead>
<tbody>
<tr>
<td>1&lt;sup&gt;st&lt;/sup&gt; tercile of ind. income</td>
<td>0.0569**</td>
<td>-0.00268</td>
</tr>
<tr>
<td></td>
<td>(0.0245)</td>
<td>(0.0177)</td>
</tr>
<tr>
<td>2&lt;sup&gt;nd&lt;/sup&gt; tercile of ind. income</td>
<td>0.0151</td>
<td>-0.0270*</td>
</tr>
<tr>
<td></td>
<td>(0.0228)</td>
<td>(0.0163)</td>
</tr>
<tr>
<td>3&lt;sup&gt;rd&lt;/sup&gt; tercile of ind. income</td>
<td>-0.0141</td>
<td>0.0187</td>
</tr>
<tr>
<td></td>
<td>(0.0144)</td>
<td>(0.0140)</td>
</tr>
<tr>
<td>(N)</td>
<td>68160</td>
<td>111300</td>
</tr>
<tr>
<td>(N) groups</td>
<td>7330</td>
<td>11660</td>
</tr>
</tbody>
</table>

Standard errors in parentheses. Standard errors are bootstrapped using 499 replications and CCHS replicate weights provided by Statistics Canada.

\(^* p<0.15, \text{ }^* p<0.1, \text{ }^** p<0.05, \text{ }^*** p<0.01\)

5.2 Coupled in the year prior to the shock

In this sub-section, we discuss results from and implications of the second definition of couple families. Under this definition, the sample is divided into two groups based on couple status in the year prior to diagnosis.

Table 4. Estimated effects on being coupled (measured as 0 or 1) after diagnosis.

<table>
<thead>
<tr>
<th></th>
<th>Male</th>
<th>Female</th>
</tr>
</thead>
<tbody>
<tr>
<td>NOT coupled before shock</td>
<td>0.0183</td>
<td>-0.0347*</td>
</tr>
<tr>
<td></td>
<td>(0.0345)</td>
<td>(0.0202)</td>
</tr>
<tr>
<td>Coupled before shock</td>
<td>0.0206*</td>
<td>0.00919</td>
</tr>
<tr>
<td></td>
<td>(0.0111)</td>
<td>(0.00951)</td>
</tr>
<tr>
<td>(N)</td>
<td>68160</td>
<td>111300</td>
</tr>
<tr>
<td>(N) groups</td>
<td>6970</td>
<td>11290</td>
</tr>
</tbody>
</table>

Standard errors in parentheses. Standard errors are bootstrapped using 499 replications and CCHS replicate weights provided by Statistics Canada.

\(^* p<0.15, \text{ }^* p<0.1, \text{ }^** p<0.05, \text{ }^*** p<0.01\)

On one hand, this definition mitigates the sample selection issue since switchers are distributed across two different groups based on their couple status one year before the diagnosis. On the other hand, this introduces a technical effect of a new tax-filing family member. As we
mentioned above, there is evidence of endogeneity of coupled status, which indicates that this technical effect may influence the results.

Table 4 illustrates the endogeneity of marital status for the two groups considered in this section. In particular, the probability of being coupled is, on average, 2% higher and statistically significant at the 10% level among diagnosed coupled before the shock males. For non-coupled males, the effect is still positive but statistically insignificant. The estimate for non-coupled females is around -3.5%.

Appendix Table A.2 reports average treatment effects on the treated for the individual income components using the second definition of couple status. The estimates for labour income losses now vary between $7,200 – $3,200 while for the total income they vary between $4,000 – $2,600. Table 5 below presents analogous results for family income. In the latter, the effects are qualitatively the same as in Table 2. Hence, it seems that the technical effect from the endogeneity of couple status does not affect our core estimates in any significant way.

**Note:** standard errors are bootstrapped using 499 replications. Range spikes represent 90% CIs. “F” stands for “Females”, while “M” stands for “Males”.

**Figure 6.** Estimated effects on the difference between family and individual total incomes by income terciles.
Table 5. Average treatment effects on the treated on family income, regressions in levels.

<table>
<thead>
<tr>
<th></th>
<th>Family Income</th>
<th>Scaled Family Income</th>
<th>Scaled After-Tax Family Income</th>
<th>Family minus Individual Income</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Male</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NOT coupled before shock</td>
<td>-4617.2 (3822.8)</td>
<td>-3800.9 (2876.1)</td>
<td>-2378.2 (2184.4)</td>
<td>-674.3 (3159.4)</td>
</tr>
<tr>
<td>Coupled before shock</td>
<td>402.4 (2321.5)</td>
<td>943.8 (1510.3)</td>
<td>1119.0 (1063.7)</td>
<td>3021.1** (1396.0)</td>
</tr>
<tr>
<td>\textit{N}</td>
<td>68160</td>
<td>61470</td>
<td>61470</td>
<td>68160</td>
</tr>
<tr>
<td>\textit{N groups}</td>
<td>6970</td>
<td>6270</td>
<td>6270</td>
<td>6970</td>
</tr>
<tr>
<td><strong>Female</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NOT coupled before shock</td>
<td>-2197.4 (2436.6)</td>
<td>-2719.0^ (1848.4)</td>
<td>-2164.5^ (1331.9)</td>
<td>1017.1 (1852.5)</td>
</tr>
<tr>
<td>Coupled before shock</td>
<td>-5312.6*** (1793.8)</td>
<td>-3631.3*** (1103.0)</td>
<td>-2508.7*** (801.1)</td>
<td>-1882.4 (1637.9)</td>
</tr>
<tr>
<td>\textit{N}</td>
<td>111300</td>
<td>97690</td>
<td>97690</td>
<td>111300</td>
</tr>
<tr>
<td>\textit{N groups}</td>
<td>11290</td>
<td>9890</td>
<td>9890</td>
<td>11290</td>
</tr>
</tbody>
</table>

Standard errors in parentheses. Standard errors are bootstrapped using 499 replications and CCHS replicate weights provided by Statistics Canada. ^ p<0.15, * p<0.1, ** p<0.05, *** p<0.01
Figure 6 confirms that our main results are robust to the choice of definition. Specifically, the results for wives or female partners (of an ill person) are consistent with the added worker effects in the middle of the husbands’ income distribution, while the results for husbands or male partners are consistent with the caregiver effect in the middle of the income distribution.

Later iterations of the analysis could also reveal if there is a selection among people who split up or get married following the health shock, e.g., if changes in family income are different between people who change marital status in control and treatment groups.

6. Conclusion

Negative health shocks can be very devastating for households, threatening their financial stability. Understanding how different insurance mechanisms work and through what channels is of paramount importance. Most research, however, focuses on labour market participation and income, family income, or social insurance receipt; the literature largely ignores the possible heterogeneity of intra-household substitution across the income distribution and income components. Also, selection and endogeneity issues related to marital status appear to be important and should be considered when estimating the effects of health shocks on family income. In this study, we try to fill this gap by utilizing a subset of administrative family tax records linked to Cancer registry files and the Canadian Community Health Survey.

Following Fadlon & Nielsen (2021) we use a novel matching methodology to address the endogeneity of health shocks born by the differences in ex-ante expectations about future health. In particular, we match individuals diagnosed with cancer to similar individuals with diagnosis five years later. Using the matched sample, we estimate a two-way fixed-effects model for various income components separately for people based on marital (couple) status. We use two definitions of being coupled: based on a 10-year period around cancer diagnosis and based only on one year before the diagnosis. First, we find that the average treatment effect on the treated (loss) on individual labour income is estimated at around 3,200 – 7,200 CAD (in 2019 prices). Second, we find that the decrease in labour earnings is considerably but not fully mitigated by social insurance for both genders and by non-labour income for the diagnosed non-coupled males.
Third, the family income of coupled diagnosed males seems to be better insured than the family income of non-coupled males. This is primarily driven by the increase in income of unaffected members of the couple family of diagnosed males who are in the middle of the pre-diagnosis individual total income distribution. The result is consistent with the added worker effect for the healthy female partners. The reverse is true for diagnosed coupled females in the second tercile of income distribution which is consistent with the caregiver effect for their male partners. The findings also imply that the observed added-worker effect for (healthy) wives is originating from the last two terciles of survival probabilities (moderate and least severe cancers), while the caregiver effect for (healthy) husbands is originating from the first two terciles (moderate and most severe cancers). In future analyses, it might be worthwhile to focus only on the moderate to most severe cancer types.

Furthermore, we show that there are second-order effects of a cancer diagnosis. In particular, we show that marital status is endogenous, with positive effects on coupled status for previously non-coupled males, and negative effects for previously non-coupled females. Finally, using two alternative sample stratifications by marital status, we demonstrate that our main findings are not robust to possible selection and endogeneity effects.
References


Statistics Canada. Table 13-10-0158-01. Age-specific five-year net survival estimates for primary sites
of cancer, by sex, three years combined
https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=1310015801


Employment benefits and job retention: Evidence among patients with colorectal cancer. *Cancer
Appendix

Table A.1. Algorithm used to eliminate duplicate tumours from IARC TMF.

| Rule 1: | When there is more than one tumour in a subset keep the tumour with the highest behaviour/site rank (see Table 35b below), if more than one tumour has the same rank keep the tumour with the earliest Date of diagnosis. If more than one tumour has the same Date of diagnosis, then the tumour with the lowest Tumour reference number, Tumour patient identification number and Tumour reporting province/territory is kept. |
| Logic | For a given patient with more than one tumour: |
| For Systemic and Multicentric Tumours: | Eliminate duplicate tumours in each Specific Histology group using Rule 1 (regardless of the Site). Eliminate duplicate tumours in each Non-Specific Histology group when there is at least one tumour within Specific Histology Groups. |
| For Non-Systemic and Non-Multicentric Tumours: | - Eliminate duplicate tumours within the same Site and same Specific Histology group using Rule 1; - Eliminate duplicate tumours within the same Site and any Non-Specific Histology group using Rule 1; - Eliminate all tumours within Non-Specific Histology groups when there is at least one tumour within Specific Histology groups for the same Site; - Eliminate duplicate tumours within the same Topography group and same Specific Histology group using Rule 1; - Eliminate duplicate tumours within the same Topography group and any Non-Specific Histology group using Rule 1; - Eliminate all tumours within Non-Specific Histology groups when there is at least one tumour within Specific Histology groups for the same Topography group. |

Figure A.1. Proportion (weighted) of women diagnosed among all people diagnosed with cancer.

Figure A.2. Proportion (weighted) of women diagnosed with cancer among all diagnosed by age.

Figure A.3. Proportions of people coupled at the time of diagnosis.
Figure A.4. Averages for selected income components.
Figure A.5. Averages for income components for switchers.
Note: standard errors are bootstrapped using 499 replications. Range spikes represent 90% CIs. “F” stands for “Females”, while “M” stands for “Males”.

**Figure A.6.** Estimated effects on individual total income by terciles of survival probability.

Note: standard errors are bootstrapped using 499 replications. Range spikes represent 90% CIs. “F” stands for “Females”, while “M” stands for “Males”.

**Figure A.7.** Estimated effects on the difference between family and individual total incomes by income terciles.
Note: standard errors are bootstrapped using 499 replications. Range spikes represent 90% CIs. “F” stands for “Females”, while “M” stands for “Males”.

Figure A.8. Estimated effects on the difference between family and individual total incomes by survival probability terciles.
Note: standard errors are bootstrapped using 499 replications. Range spikes represent 90% CIs. “F” stands for “Females”, while “M” stands for “Males”.

Figure A.9. Effects on individual relative transfers and taxes (divided by average pre-treatment income) by terciles of individual income.
Table A.2.

<table>
<thead>
<tr>
<th></th>
<th>Total Income</th>
<th>Labour Income</th>
<th>Non-Labour Income</th>
<th>Transfers</th>
<th>Taxes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male NOT coupled before shock</td>
<td>-3942.9**</td>
<td>-7145.1***</td>
<td>1691.6**</td>
<td>1001.9***</td>
<td>-954.6^</td>
</tr>
<tr>
<td></td>
<td>(1860.2)</td>
<td>(1888.1)</td>
<td>(817.4)</td>
<td>(321.5)</td>
<td>(589.8)</td>
</tr>
<tr>
<td>Male Coupled before shock</td>
<td>-2618.7^</td>
<td>-3231.9***</td>
<td>-93.89</td>
<td>821.8***</td>
<td>-1041.4*</td>
</tr>
<tr>
<td></td>
<td>(1690.6)</td>
<td>(1599.4)</td>
<td>(781.7)</td>
<td>(188.9)</td>
<td>(588.6)</td>
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<td>N NOT coupled before shock</td>
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<td>68160</td>
<td>68160</td>
<td>68160</td>
<td>68160</td>
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<tr>
<td>N groups</td>
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<td>6970</td>
<td>6970</td>
<td>6970</td>
<td>6970</td>
</tr>
<tr>
<td>Female NOT coupled before shock</td>
<td>-3214.5**</td>
<td>-5449.8***</td>
<td>841.3</td>
<td>795.0***</td>
<td>-623.5*</td>
</tr>
<tr>
<td></td>
<td>(1446.1)</td>
<td>(1729.1)</td>
<td>(595.5)</td>
<td>(250.5)</td>
<td>(361.5)</td>
</tr>
<tr>
<td>Female Coupled before shock</td>
<td>-3430.2***</td>
<td>-4359.9***</td>
<td>279.8</td>
<td>562.4***</td>
<td>-800.7***</td>
</tr>
<tr>
<td></td>
<td>(771.7)</td>
<td>(830.8)</td>
<td>(239.4)</td>
<td>(146.1)</td>
<td>(212.4)</td>
</tr>
<tr>
<td>N Female</td>
<td>111300</td>
<td>111300</td>
<td>111300</td>
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<td>11290</td>
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</tbody>
</table>

Standard errors in parentheses. Standard errors are bootstrapped using 499 replications and CCHS replicate weights provided by Statistics Canada.

^ p<0.15, * p<0.1, ** p<0.05, *** p<0.01