Income Dynamics and Rent Sharing of Coworking Couples*

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Abstract

Firms pass through performance shocks to worker earnings, a phenomenon known as rent sharing that is inconsistent with perfectly competitive labor markets. In this paper I provide a novel test of monopsony power in the labor market which links rent sharing to worker mobility, by studying coworking couples, married couples who share an employer. Using Norwegian administrative data, I quantify differences in the pass-through of idiosyncratic firm shocks and find that women in coworking couples experience less generous rent sharing: at any given level of firm performance, they have lower income growth than their non-coworking counterparts. This leads to large differences in household income dynamics: coworking couples face lower average income growth and higher income risk, with substantial consequences for welfare. Firms exploit the fact that coworking couples are less mobile in order to engage in less generous rent sharing with these couples.

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1 Introduction

There is robust evidence that firms engage in rent sharing with their workers: shocks to productivity, including ones idiosyncratic to the firm, are passed on to the earnings of employees. The fact that firms are able to transmit idiosyncratic shocks, including negative ones, to worker earnings contradicts perfectly competitive models of labor markets: if markets were frictionless, workers could insure themselves against these shocks by moving to a different firm. As a result, recent work has cast rent sharing as evidence of monopsony power in the labor market, arising from frictions to job-to-job mobility, so that workers find it costly to switch firms. Firms take advantage of these frictions to exercise monopsony power when setting wages, enabling them to cut wages when times are bad.

An immediate consequence of this monopsonistic explanation for rent sharing is that firms ought to engage in price discrimination on the basis of observable differences in worker mobility. Put another way, though firms may not know the precise mobility of each worker, they should use *as much information as possible* about it when setting wages. On the other hand, research suggests that issues such as fairness concerns may constrain firms from excessive price discrimination between employees, as awareness of within-workplace inequality reduces worker satisfaction and productivity (Card et al., 2012; Breza et al., 2018; Cullen and Pakzad-Hurson, 2021; Cullen and Perez-Truglia, 2022).[1] Thus, quantifying the degree of this price discrimination is ultimately an empirical question, and one that has not been well-explored by researchers.

The goal of this paper is to investigate this question. I provide novel evidence that firms do indeed consider observable mobility differences by studying *coworking couples*: married couples who share a workplace. The rationale for this strategy stems from two facts. First, being a coworking couple is an observable feature to firms: employers generally know when two employees are married.[2] Second, coworking couples should have a lower propensity to leave their current employer because they enjoy an amenity from working together and do not want to lose it by breaking the match. Thus, firms should account for coworking couples' observably lower mobility by offering them less generous rent sharing, a form of price discrimination: for example, they should be able to pass through a larger proportion of negative firm shocks.

[1]These constraints may also be important for broader macroeconomic phenomena; see, for example, Snell and Thomas (2010), which argues that internal constraints on price discrimination between workers can explain observed patterns of wage rigidity in labor markets.

[2]It is common for organizations to require employees to disclose relationships with coworkers: see, for example, the Code of Conduct of Yara ASA, one of the largest employers in Norway, in Appendix Figure E1. Firms might also infer that two employees are married from, for example, shared bank accounts, shared addresses, or even office gossip.

Coworking couples are a common feature of the labor market: Hyatt (2019) estimates that in 2000, 11-13% of working-age American couples were coworking. Despite this, research on them has been scarce. This is in part due to data challenges: identifying coworking couples requires both linking married couples together and linking employees to their employers. In addition, obtaining a reasonable sample size of coworking couples necessitates data with universal coverage of the population of workers and firms.[3] I overcome these challenges by using high quality Norwegian adminstrative data on the universe of individuals and employers in Norway. The data include consistent identifiers for individuals and establishments that can be used to track marriages and work histories for all Norwegians over time.

To fix ideas, I begin by outlining a simple model of on-the-job search which makes clear the links between worker mobility, monopsony power, and rent sharing. A more productive firm is willing to pay more to retain workers, as a higher surplus of the match implies higher profits. However, if mobility is costly, firms will be able to mark down wages so that workers do not capture the full surplus. In this way, the setting of rent sharing between workers and firms is informative about the link between mobility and monopsony power.

I test the predictions of the model in the Norwegian data and find systematic differences in mobility and rent sharing for coworking couples, consistent with the prediction that firms respond to worker observables. First, I find large differences in job-to-job mobility for coworking couples. Workers in coworking couples are significantly less likely to move to a new employer in any given year, independent of the level of firm performance. These large differences in mobility translate into large differences in rent sharing. Using balance sheet data to construct idiosyncratic shocks to firm value-added, I estimate flexible, non-linear rent sharing schedules relating firm shocks to workers' income growth separately for coworking and non-coworking couples. I find that coworking women in particular experience persistently lower income growth for any given shock, though the difference is somewhat larger for very negative shocks, on the order of 2 log points per year for the worst 10% of firm performance shocks. That is, while both coworking men and women have lower job-to-job mobility than their non-coworking counterparts, this lower mobility only results in lower income growth for coworking women.

I investigate the reason for these stark gender differences and find that the rent sharing differences are larger for coworking wives who earn strictly less than their husbands, a possible signal to the firm that their career is less likely to be prioritized. In addition, I show that in the 5 years after their husband leaves the workplace, coworking wives are significantly

[3]For example, suppose you have a population of N opposite-sex married couples, and take a random sample of k men and k women. On average, your sample will only include $k^2/N < k$ married couples, even though everyone in the population of interest is married.

more likely to also quit than vice versa, also suggesting that firm perceptions about career prioritization may explain the gender difference in rent sharing.

My results are robust to a variety of concerns about selection bias. Consistent with the literature, my estimates of rent sharing use only income growth for stayers, i.e. workers who remain at the firm. Focusing on stayers could introduce selection bias as the observed distribution of income growth will reflect not only differences in the raises *offered* to workers of different types, but also differences in what offers workers *accept*. I correct for this by using variation induced by mass layoff events that are unlikely to reflect voluntary choices, and variation in outside options for workers. The finding that coworking women face less generous rent sharing remains robust to addressing this selection bias. I also show that my results are unlikely to be driven by systematic differences in the productivity of coworking women. Looking at women who end up marrying a coworker versus those who marry a non-coworker, I find that if anything women who marry a coworker have higher income growth before marriage, evidence against them having lower individual ability. Examining cases where the wife is the incumbent in a workplace and is joined by her husband, I find that the wife still experiences lower income growth after her husband joins, evidence against nepotism or poorer match quality driving the results.

To assess the consequences of being in a coworking couple on household welfare, I then turn to an analysis of the dynamics of household income for coworking and non-coworking couples. In particular, I examine differences in the growth rate of household income and its riskiness between these groups. I find that coworking couples have significantly lower average household income growth than their non-coworking counterparts, on the order of 23% lower growth per year, even after controlling for a full set of establishment-by-year fixed effects.

Next, I show that coworking couples also face greater household income *risk*. Even if there were no difference in the individual income risk of coworking couples, we would expect them to face higher household income risk simply because their individual incomes are more correlated, which I term a "covariance effect". I present an intuitive decomposition of household income risk into components corresponding to the variance of each spouse's individual income and the covariance between them. Coworking couples face substantially greater risk in their income growth, on the order of 57% higher annual variance. Decomposing this, about half of the difference in risk stems from greater risk for coworking wives, 30% from the covariance effect, and the remaining 20% from higher risk for coworking husbands, consistent with the finding that differences in rent sharing are concentrated among wives.

The differences in household income dynamics are qualitatively consistent with the observed differences in rent sharing for coworking and non-coworking couples. But, are these differences in rent sharing quantitatively important? I show that they are. In particular, I show that variation in firm performance and differences in rent sharing can account for 44% and 10% of the observed differences in household income growth and risk respectively. Thus, these differences in rent sharing have a material impact on household income dynamics. For workers, job-to-job mobility serves as a form of insurance against idiosyncratic firm shocks, and coworking couples are significantly less insured against this source of income risk.

The observed differences in income growth and risk are substantial, and a simple Lucas (1987) style welfare calculation implies that equalizing income streams of coworking and non-coworking couples would be equivalent in utility terms to a transfer of 1.8% of annual consumption. Whether this figure reflects true welfare differences depends on the relative size of the amenity value of coworking versus frictions in the labor market. In a frictionless market, welfare must be equalized across workplaces, meaning that the differences in consumption-equivalent welfare estimate a willingness-to-pay for the amenity of working with your spouse. If there are no such amenities, then it must be that these couples exist solely due to frictions in the labor market preventing them from diversifying their income risk, so that these differences reflect real dispersion in realized utility.

This paper contributes to the extensive literature on rent sharing between firms and workers, which seeks to quantify and explain the extent to which firms transmit changes to their productivity onto the wages of their workers. Most empirical estimates of rent sharing have used firm and worker microdata to study the covariance between firm-specific productivity and wages (Guiso et al., 2005; Friedrich et al., 2019; many others documented in the review by Card et al., 2018), the approach that I follow most closely here. Other estimates have used structural models (Lamadon et al., 2022; Balke and Lamadon, 2022), or exogenous shocks to firm performance like patents (Kline et al., 2019), trade shocks (Garin and Silverio, 2022), or oil prices (Cho and Krueger, 2022). These papers generally find robust evidence for rent-sharing, rejecting competitive models of the labor market. Theoretical work on the reasons for rent sharing has focused upon monopsony power, in which workers have heterogeneous mobility costs or amenity values over employers, meaning that firms have some pricing power (Card et al., 2018; Lamadon et al., 2022; Balke and Lamadon, 2022).[4] Relative to most empirical work estimating rent sharing, which generally estimates a single elasticity between firm performance and worker earnings for the full sample, in this paper I estimate a flexible, nonlinear rent sharing schedule, and show that substantial differences in rent sharing exist even between worker at the same firm.[5] I also provide novel evidence for an

[4]More generally, the idea that the worker's outside option is an important determinant of wages has a long history. Recently, there has been a renewed interest in the consequences of this channel for the degree of monopsony power in labor markets (Jarosch et al., 2019; Bagga, 2023; Sharma, 2023).

[5]There are some papers which seek to estimate how bargaining power and rent sharing differ across different demographic groups, particularly gender (Card et al., 2016; Roussille, 2022).

important theoretical prediction of monopsonistic models of rent sharing, that firms should take advantage of as much information as is available to them about workers' propensity to move when setting rent sharing schedules.[6]

This paper also contributes to the literature on the sources of income growth for workers. There has been a great deal of work both theoretical and empirical on the importance of job-to-job mobility (Topel and Ward, 1992; Burdett and Mortensen, 1998; Postel–Vinay and Robin, 2002; Blanco et al., 2022, to name just a few), internal promotions (Lazear and Rosen, 1981; Baker et al., 1994; Gibbons and Waldman, 1999; Bronson and Thoursie, 2021), or both together (van der Klaauw and Dias da Silva, 2011; Bagger et al., 2014; Frederiksen et al., 2016) for wage growth, finding an important role for both.[7] This paper contributes to this literature by considering the interaction of these two sources of wage growth and showing that observable differences in worker mobility lead to substantial difference in within-firm earnings growth.[8] Another novel feature of this paper is that it provides evidence for how differences in rent sharing are linked to differences in income growth: in particular, that lower income growth on average arises because less mobile workers do worse specifically when their firm is performing poorly, and are not compensated accordingly when their firm does well.

Finally, this paper contributes to a very small literature on the economic consequences of being in a coworking couple. There has been some work in personnel economics on the role of the workplace as a marriage market, including quantifying factors which lead to more workplace marriages (Mansour and McKinnish, 2018; McKinnish, 2007; Svarer, 2007; Moen and Sweet, 2002), but with the exception of Zinovyeva and Tverdostup (2021), who study the role of coworking couples in explaining spousal wage gaps, no papers have actually examined how coworking couples differ from their non-coworking counterparts. In this paper I document substantial differences in the welfare-relevant dynamics of household income for coworking couples, as well as a series of other facts about the formation, characteristics, and dynamics of these couples.

The rest of the paper is structured as follows. Section 2 describes the Norwegian admin-

[6] One paper which does seek to examine the link between pay and worker observables is Roussille and Scuderi (2022), which studies a unique online job board where firms must post a "bid" salary when seeking to interview prospective job seekers. They find no evidence that firms tailor these bids to observable characteristics of workers, though they only estimate heterogeneity on a set of estimated discrete worker types, which may not correspond to the characteristics actually considered by employers.

[7] There is also a literature on the returns to specific human capital, which takes the opposite view that job-to-job mobility can also have a negative direct effect on earnings by depreciating a worker's firm, occupation, or industry-specific human capital. See, for example, Altonji and Shakotko (1987), Topel (1991), Dustmann and Meghir (2005), Buchinsky et al. (2010), among others.

[8] Another paper in this spirit is Caldwell and Harmon (2019), which shows that when workers obtain information about outside options through their social networks, they are able to leverage it for wage increases even if they do not move.

istrative data and presents some facts about the frequency and characteristics of coworking couples in Norway. Section 3 presents a simple model of rent sharing that makes predictions about the relationship between mobility and rent sharing. Section 4 tests these predictions by estimating differences in rent sharing and mobility for coworking couples. Section 5 shows that the rent sharing estimates are robust to various concerns about selection bias. Section 6 documents that coworking couples face large differences in income growth and risk. Section 7 connects these differences in rent sharing and income dynamics by showing that differences in rent sharing can explain a large part of the differences in income growth and risk for coworking couples, and considers the welfare consequences of being in a coworking couple. Section 8 concludes.

2 Data

The data for this project come from a set of administrative registers maintained by Statistics Norway, linked through unique identifiers for individuals, firms and establishments.

On the household side, I begin with a longitudinal dataset on the universe of Norwegian residents from 1993-2015, linked to tax records. In each year, this dataset provides demographic variables including age, gender, educational attainment, and marital status (and the identity of the spouse), as well as high quality data on individual income from the tax records. By using the unique individual identifiers provided in the data, I am able to identify married couples and follow them over time.

I link the individual-level data with matched employer-employee data spanning all employment relationships in Norway from 1995-2014. This dataset provides a unique set of firm and plant (establishment) level identifiers that allow me to connect workers with their workplaces over time. The data contain detailed start and end dates for each employment spell, as well as firm, plant, and match-level variables such as sector, location, and an additional measure of worker compensation from firm payrolls.

To measure firm performance, I use a register of firm balance sheets, also spanning 1995-2015, which provides data on firm assets, liabilities and operating income and costs at the firm level for non-financial private sector firms in Norway. Finally, in order to identify firm ownership for some analyses, I use a shareholder registry that identifies the owners and ownership shares of all limited-liability companies in Norway from 2004-2015.

I use the unique individual, firm, and plant level identifiers in these datasets to link married couples together and workers to their employers over time. The sample period for the linked dataset spans 1995-2014. For workers with more than one employer in a year, I assign them the employer from which they had the highest earnings. I limit the sample to working-age (25-60) individuals with continuous records in the panel.[9] For the purposes of estimating rent sharing between firms and workers, I also identify *continuers*, workers who remain at the same plant this and last year.

I define a *coworking couple* as a married couple employed at the same plant. I define coworking at the plant rather than the firm level to better capture the idea of actually sharing a workplace. For brevity, and because I will frequently be comparing differences between individuals who share a workplace with their spouse and those who do not, I will sometimes abbreviate these two groups as CWC and non-CWC.[10]

The quality and coverage of these administrative data present several advantages over data available for other countries. First, the universal coverage and presence of unique individual, spousal, and plant level identifiers allow me to both link married couples together and link workers to employers, both of which are necessary in order to obtain a reasonable sample of coworking couples. The income variables in the household register cover the universe of all Norwegians subject to income taxes, including those at the top of the income distribution, and are collected by the tax authority, alleviating concerns about censoring and measurement error that arise in survey data. Finally, the data have a long and consistent panel dimension, spanning nearly 20 years, permitting a rich characterization of the dynamics of income for coworking and non-coworking couples over the life cycle, allowing me to address persistent individual and firm level heterogeneity using standard fixed effect methods, and alleviating concerns about sample attrition that arise in household surveys such as the PSID.

2.1 Facts About Coworking Couples

Before using coworking couples to study the relationship of rent sharing to worker mobility, it is important to understand how similar these couples are to the population as a whole. Table 1 presents summary statistics for coworking and non-coworking households in the data. Here I limit the sample to couple-years in which both partners are continuers, that is, they stay at their jobs. Here, we see preliminary evidence that coworking couples have lower income growth and higher risk: household and individual income growths for these couples has a lower mean and median and a higher variance for CWC compared to non-CWC. On other dimensions, coworking couples look quite similar to the population as a whole: they are very close in average age, fertility, and levels of income. Coworking couples are, however, slightly more assorted: coworking men have slightly lower income than their non-coworking

[9] So, while I allow for an unbalanced panel as workers age in and out of the sample (or die), I drop individuals who exit and then re-enter the data. This generally is caused by extended stays abroad, and amount to just 0.17% of observations.

[10] For more details on the datasets used and the data construction process, see Appendix A.

counterparts, whereas coworking women have slightly higher income.[11]

Table 1: Descriptive Statistics

	Non-Coworking			Coworking		
	Mean	Median	Variance	Mean	Median	Variance
Δ log HH Inc	.0321	.0292	.0189	.0263	.0255	.0366
Δ log Wife Inc	.0368	.0296	.0913	.0282	.0266	.117
Δ log Husband Inc	.0269	.0248	.052	.0217	.0212	.0808
Age Wife	43.1	43	71.5	43.8	44	71.5
Age Husband	45.3	46	72.2	46.3	47	70.9
HH Inc (1000 2011 USD)	155	141	5,132	154	140	5,694
Wife Inc (1000 2011 USD)	59	55.5	923	61.7	58	1,105
Husband Inc (1000 2011 USD)	95.7	83.2	3,444	92.2	80.8	3,219
Wife Plant Size	387	52	1,494,540	546	41	3,186,796
Husband Plant Size	376	55	2,127,185	525	34	3,125,160
Kids Under 5	.375	0	.546	.354	0	.541
Kids Under 13	.968	1	1.18	.914	0	1.23
Observations	4,844,057					

Note: Summary statistics for dual-continuer households with both spouses aged 25-60. Income levels deflated using Norwegian CPI and converted to 2011 USD.

To get a better sense of the frequency of coworking couples across the income distribution, in Figure 1 I rank all married couples into percentiles of household income, and plot histograms of these percentiles separately for coworking and non-coworking couples. Coworking couples are somewhat overrepresented among the richest and poorest households, but are quite common throughout: this is clearly not a phenomenon that is present in only one specific part of the distribution.

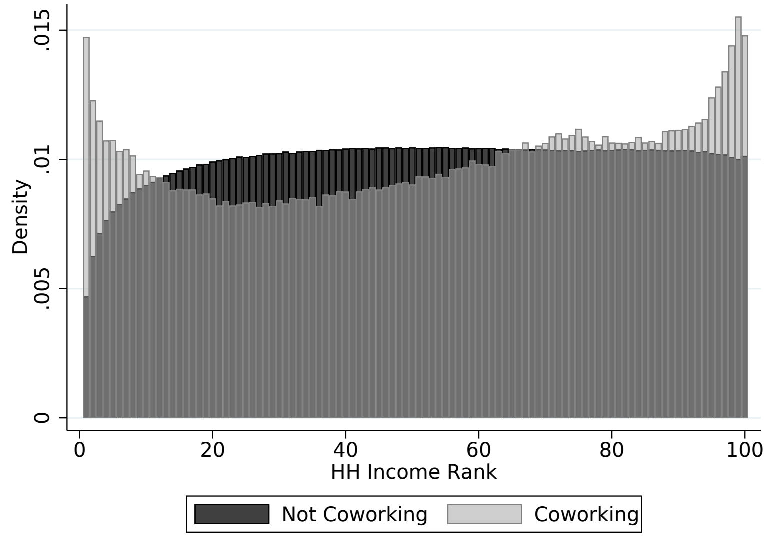
Overall in my sample, about 8% of dual-employed couples are coworking in any given year, a substantial fraction of Norwegian couples.[12] Reassuringly for external validity, the prevalence of coworking couples in Norway is quite similar to the 11-13% for the United States estimated by Hyatt (2019).[13] Coworking couples are relatively similar in terms of the average age of both spouses and in terms of household and individual income, and are quite

[11]Note that plant sizes for coworking husbands and wives are not equal because coworking is defined as sharing any plant in a year, whereas the given plant size is for the highest-paying plant. As shown in Appendix Table E1 and Figure E2, my results are robust to limiting the sample to couple-years with only one job.

[12]For additional context on the characteristics of coworking couples in Norway, see Appendix B. Appendix Figure E3 plots the proportion of coworking couples over time in the sample. Coworking rates have declined over time, but remain quite common throughout the sample period.

[13]Given that Hyatt's estimates are for the year 2000, and the frequency of coworking couples have declined somewhat over time, the rates are even more similar: 9% of couples were coworking in Norway in 2000.

Figure 1: Household Income Rank by Coworking



Note: Histograms of percentiles of the household income distribution for coworking and non-coworking couples. Ranks are computed on a year-by-year basis.

common throughout the income distribution, meaning that their existence is not solely a feature of a specific kind of job or household.

3 A Model of Rent Sharing

In this section I formalize the mechanism by which differences in mobility for coworking couples lead to less generous rent sharing by presenting a simple model which makes sharp predictions about the relationship between firm performance and wages. In particular, I show that:

1. Firms engage in rent sharing: there is a positive correlation between firm productivity and wages.

2. Worker mobility matters for rent sharing: workers for whom mobility is costlier receive lower wages for any given firm productivity level.

The key features of the model are on-the-job search and costly mobility: while employed, workers receive outside wage offers, which disciplines the monopsony power of their employers. However, there are costs to mobility which vary between workers, which firms take advantage of.

3.1 Setup

Suppose we begin with a population of workers employed at a set of firms. Workers and firms have linear utility in wages and profits respectively. Workers vary in how costly it is for them to switch firms, parametrized by a pecuniary cost c. The timing of the model is as follows:

1. Firms realize a productivity shock which translates to a potential surplus π, common across workers at that firm. There are no scale effects or complementarities: the firm treats each worker independently. π is observed by both the firm and the worker.

2. Workers draw an outside wage offer w_o from a distribution $F(\cdot)$. I abstract from modeling poaching firms and assume $F(\cdot)$ is exogenous.[14]

3. Firms offer workers a wage w, taking into account the surplus of the match π, the mobility type c of the worker, and the distribution but *not* the specific realization of outside offers.

4. Workers decide whether to stay at their current firm or accept the outside offer. If they switch, they must pay their mobility cost c, hence receiving $w_o - c$.

5. If the worker stays, production is realized and split according to the offered w. If not, the firm produces nothing and earns no profits.

It is worth noting that steps 2 and 3 can occur in either order: because firms know the *distribution* of workers' outside offers but not the specific realizations of these offers, the wage they offer depends only on the surplus and that worker's mobility cost c. Workers also know this, so conditional on the surplus they can perfectly predict the wage the firm will offer to them.

3.2 Solving the Model

3.2.1 The Worker's Problem

Note that the worker makes no decisions under uncertainty here: they are choosing between known inside and outside offers and will pick the higher one (net of mobility costs). Then,

[14]It would be straightforward to endogenize the distribution of outside offers by modeling these offers as coming from other profit-maximizing firms who draw a surplus π_o upon matching with a worker. However, it is not clear that introducing this complication provides meaningful additional insight into the relationship between mobility and rent sharing. Alternatively, we can think of the model as representing firms in one small sector of the economy, while outside offers come from a combination of both private firms and government agencies which may not be profit maximizers. This seems especially plausible in Norway, where the public sector makes up a large share of employment.

from the firm's perspective, the probability that a worker stays if they are offered a wage w is given by

$$P(w_o - c \leq w) = F(w + c)$$

Where $F(\cdot)$ is the cdf of outside offers. The higher the wage the firm offers, the more likely it is to beat the worker's draw of w_o, so that the worker stays. The higher the cost of mobility c, the harder it is for the worker to move, so they are more likely to stay.

3.2.2 The Firm's Problem

The firm's problem is to choose a wage w to maximize expected profits. Profits are $\pi - w$ if the worker stays and 0 if they leave, so the firm's problem is

$$\max_{w}(\pi - w)F(w + c)$$

The firm trades off lower profits from increasing the wage offer with a higher probability of retaining the worker. Solving this yields the first order condition

$$w = \pi - \frac{F(w + c)}{f(w + c)} \tag{1}$$

That is, the offered wage is the surplus marked down by the Mills ratio of the distribution of outside offers. Assuming the Mills ratio is increasing and convex, as is the case for common distributions such as the Lognormal, it is clear that:

1. Wages are an increasing but concave function of surplus: there is rent sharing between workers and firms.[15]

2. Wages are decreasing in the mobility cost c: if coworking couples have a higher c, they will receive a larger markdown relative to their non-coworking counterparts.

The intuition here is clear: the higher the surplus, the higher the potential profits, so the firm is willing to pay more to retain the worker and produce. However, the higher the wage offer, the less likely it is to be beaten by an outside offer, so there is less incentive to continue raising the wage. The higher a worker's c, the less likely they are to receive an offer large enough to overcome this cost, so there is less incentive for the firm to offer a higher wage. Thus, (1) highlights the role of mobility in rent sharing: firms share rents because it is in

[15] Note that I constrain offered wages to be positive. Theoretically, if mobility costs were high enough or the surplus low enough, it could be the case that $\pi - \frac{F(c)}{f(c)} < 0$, in which case the firm would want to offer workers a negative wage. I rule out this case, assuming that workers can always quit into unemployment and earn 0.

their interest to retain workers when productivity is high. If firms know that a worker is less likely to move, they will engage in less generous rent sharing.[16]

4 Coworking Couples Experience Less Generous Rent Sharing

In this section I show that the rent sharing relationship between firms and workers differs between coworking and non-coworking couples in a way that is consistent with the theoretical predictions of the model. I begin by verifying that coworking couples are systematically less mobile than non-coworking couples, suggesting that firms can exercise a greater degree of monopsony power over them. I then show that coworking women in particular experience persistently lower income growth at every level of firm performance by estimating nonlinear rent sharing schedules.

4.1 Measuring Firm Performance

I follow Guiso et al. (2005) and Friedrich et al. (2019) in measuring shocks to firm performance as the unexplained growth of log value added per worker. I measure log value added per worker at the firm level using the balance sheet data, residualize it on log firm size and industry by year fixed effects, and take first differences. Value added is defined as revenues net of operating costs *except* payments to labor and capital. This measure is appealing in the context of rent sharing because it captures the total surplus created by the firm in excess of the value of intermediate inputs, which is precisely the size of the "pie" that can be split between labor, capital, and the firm owner as a result of the firm's production–the amount of the rents to be shared.

4.2 Coworking Couples are Less Mobile

To show that firms engage in different rent sharing relationships with coworking couples because they are less mobile, I must first establish that coworking couples are in fact less mobile. I focus on a sample of person-years in which a worker holds only one job at a time. My definition of mobility is a binary variable for whether a worker switches employers in this year: that is, it is an indicator for a job-to-job transition.[17]

[16] The simple model I present here relates productivity and wage *levels*, but can be easily extended to explain the relationship between productivity shocks and income growth rates by introducing multiple periods: see Appendix Section C.

[17] Note that if a worker separates from their employer and does not find a new job in this year, this indicator will be zero. The results of this section are quite similar if we instead take any job ending as the

First, I consider level differences in mobility between coworking and non-coworking couples. In particular, I estimate linear probability models of the form

$$\text{Move}_{it} = \beta CWC_{it} + X_{it}'\delta + \varepsilon_{it} \tag{2}$$

Where X_{it} is a set of controls for characteristics of the worker, their spouse, and the employer in the previous year. Table 2 reports the results of this regression. I find that coworking couples are significantly less likely to switch employers in a given year, at about 1 percentage point less likely off of an average of 5 percent, or about 20% less likely. Again, this result holds even after controlling for plant (column 3) or a full set of plant by year (column 4) fixed effects. Thus, coworking couples are significantly less likely in all years to have a job-to-job transition event.

Table 2: Probability of Job-to-Job Transition by Coworking

	(1) Switch Job b/se	(2) Switch Job b/se	(3) Switch Job b/se	(4) Switch Job b/se
Coworking	-0.018***	-0.014***	-0.009***	-0.009***
	(0.000)	(0.000)	(0.000)	(0.000)
Controls	No	Yes	Yes	Yes
Prev Log Inc	No	No	Yes	Yes
Plant FE	No	No	Yes	No
Plant-Year FE	No	No	No	Yes
R-Sq	0.000	0.009	0.066	0.230
Mean Dep. Var	.0494	.0492	.0492	.0493
Observations	15,528,580	15,525,677	14,839,456	14,176,764

Note: Standard errors in parentheses, clustered at the couple level. Controls for age fixed effects, education, location of both spouses, year, log income last year, number of kids under 13, and plant fixed effects. Sample of married workers aged 25-60 who worked at either 1 or 2 plants this year.

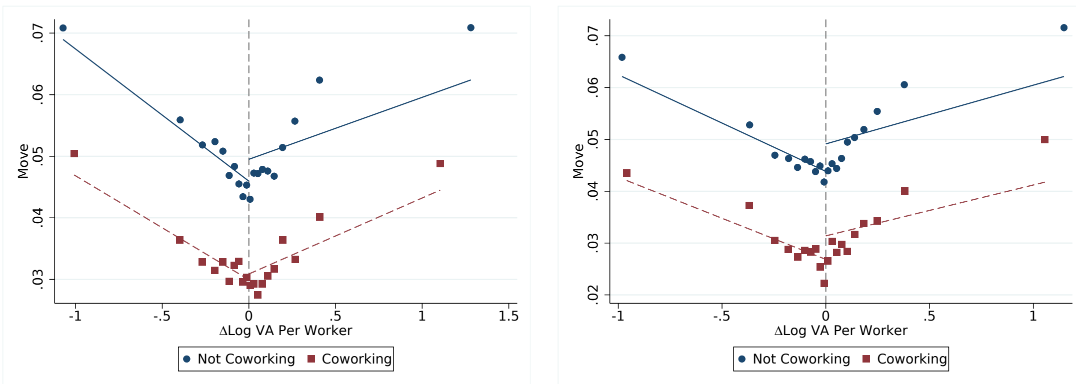
Perhaps more relevant to firm wage setting than level differences in mobility is the sensitivity of mobility to firm performance. Figure 2 presents binned scatterplots of the probability of a job-to-job transition against quantiles of firm performance shocks by coworking status, with Panel (a) displaying men and Panel (b) women. For any given shock to firm productivity, coworking couples are less mobile than non-CWC. The size of this gap is quite similar across the distribution of firm performance: lower mobility is a fixed feature of coworking couples. This gap is quite sizeable in all cases: for example, the most mobile

definition of mobility: see Appendix Figure E4.

coworking women are about as likely to move as the least likely non-coworking women.

Figure 2: Mobility by Firm Performance

(a) Men (b) Women



There is also a non-monotonicity in the relationship between mobility and firm performance. When the firm receives a negative shock (value added growth is negative), there is a negative relationship between performance and mobility, as would be expected: workers are more likely to leave underperforming firms. However, when the firm shock is positive, the relationship betweeen performance and mobility becomes positive: workers at firms with higher producivity growth are also more likely to leave. This pattern has been observed before in the literature and may reflect a process of creative destruction as quickly growing firms reinvent themselves.[18] While this pattern is interesting and may merit further study, it is not the focus of my analysis. For the purposes of this paper, it suffices to establish that coworking couples are consistently less mobile regardless of firm performance, and this difference is quite large.

4.3 Estimating Differences in Rent Sharing

The differences in the relationship between household income growth and firm performance for coworking and non-coworking couples suggest that coworking couples should experience systematically different rent sharing relationships with their employers. In this section I seek to estimate these differences. I choose to remain agnostic about the shape of the rent-sharing relationship for both coworking and non-coworking couples and estimate a flexible relationship between firm performance and individual income growth in the spirit of a binned

[18]See, for instance, Borovickova (2016). This pattern could also be generated by models in which earnings growth for incumbent workers diverges over time from their potential earnings in the wider labor market, such as Blanco et al. (2022). Workers at productive firms may be incentivized to search for better matches elsewhere.

scatterplot.[19] In particular, I first rank workers into deciles by their realized firm performance shock. Then I estimate models that allow for differences in income growth for coworking and non-coworking couples at each decile of firm performance. In particular, I run regressions of the form:

$$\Delta y_{it} = \beta_0 CWC_{it} + \sum_{q=1}^{9} (\beta_1^q d_{it}^q + \beta_2^q d_{it}^q \times CWC_{it}) + X_{it}'\delta + \varepsilon_{it} \tag{3}$$

Where d_{it}^q is an indicator for worker i being at a firm in the qth decile of performance. I omit the top decile of firm performance, so that the coefficients should be interpreted as income growth relative to workers at the best-performing firms. The main coefficients of interest are the β_2^q, which measure the difference in income growth for coworking couples conditional on a level of firm performance. This specification innovates on the usual rent sharing literature by allowing for arbitrary nonlinearity in the rent sharing relationship for both groups and, by controlling for plant fixed effects, allowing for heterogeneous rent sharing between coworking couples and non-CWC at the same firm.[20] By using growth rate based specifications, I address concerns about persistent differences in individual productivity or the kinds of firms coworking couples sort into: I study the response of income *growth* to *innovations* in firm performance, eliminating fixed sources of heterogeneity in productivity that would be a concern in levels. In order to focus more closely on the rent sharing relationship between worker and firm, I estimate this model with *individual* income rather than household as the dependent variable. To account for potential gender differences in the relationship between workers and firms, I estimate the model separately for men and women. Consistent with the rent sharing literature, I focus on continuers, workers who have stayed at their current firm for at least a year.

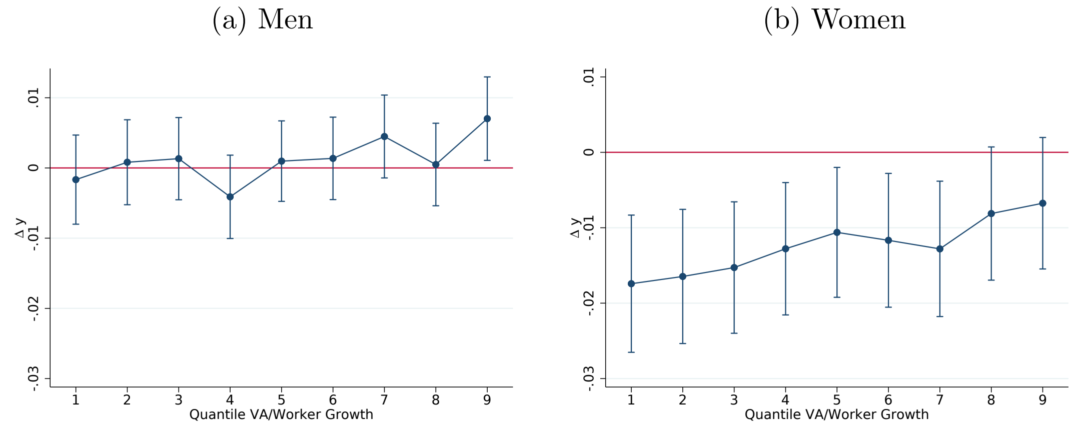
In Figure 3 I plot the β_2^q coefficients from Equation (3), the differences in income growth for coworking vs non-coworking couples at each level of firm performance. Panel (a) presents the estimates for men and Panel (b) for women.

For men, we observe no significant differences: coworking and non-coworking men have similar average income growth conditional on firm performance. For women, on the other hand, substantial differences emerge. At all deciles, coworking women have lower estimated income growth than their non-coworking counterparts. These differences are on the order of 1-2 log points, which is quite large given that the average income growth of wives in the sample is around 3-4% in Table 1. There is also some suggestive evidence that the gap between

[19] For the sake of external validity, Appendix Table E2 presents the estimated log linear rent sharing elasticity usually estimated in the rent sharing literature. The estimate of approximately 0.03 is in line with past studies in Scandinavia using firm level microdata (Card et al., 2018).

[20] It is not possible to control for a full set of plant-by-year fixed effects here because the variation in firm performance is measured at a firm-by-year level.

Figure 3: Rent Sharing Estimates by Gender



Note: Plotted coefficients are the β_2^q, the interaction of coworking with deciles of firm performance $q_{it}^{\Delta VA} \times CWC_{it}$.

coworking and non-coworking women is largest for the lowest deciles of firm performance, and shrinks somewhat as firm performance improves, though it is not possible to rule out uniformly lower rent sharing below the top decile. The exception is the top decile: β_0, the coefficient on coworking alone, can be interpreted as the difference in rent sharing between coworking and non-coworking women at firms in the top decile. I estimate that $\hat{\beta}_0 = 0.002$, a positive but insignificant coefficient. This implies that coworking and non-coworking women in the top decile of firm performance have quite similar income growth, whereas coworking women in the rest of the distribution experience substantially lower income growth.[21]

4.4 Gender Differences in Rent Sharing

I shown that differences in worker mobility observable to employers indeed leads to differences in rent sharing, as would be predicted by monopsonistic models of wage setting. Coworking women are significantly less likely to make job-to-job transitions, and also receive less generous rent sharing, effectively getting lower raises for a given firm productivity shock. The fact that coworking men do not experience differential rent sharing despite also being less mobile than their non-coworking counterparts, however, suggests that there may be gender-specific factors at play that complicate the relationship between mobility and rent sharing.

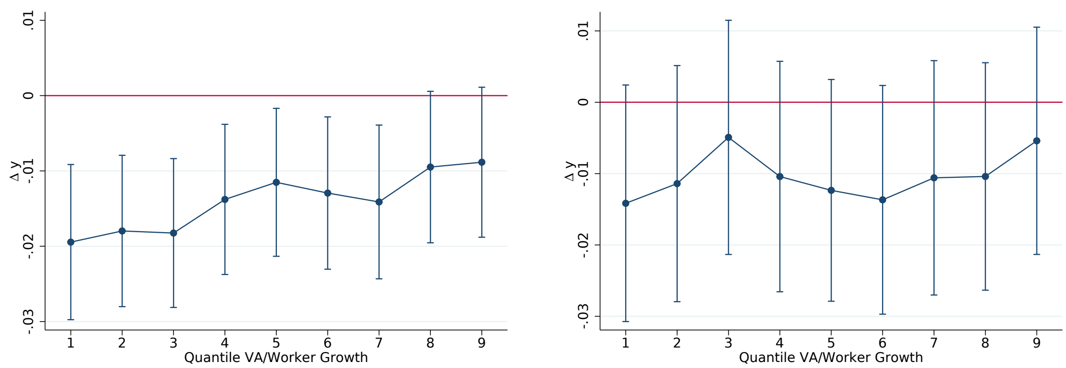
In this section I present suggestive evidence that these gender differences in rent sharing are related to the relative income of the husband and wife. In particular, differences in rent

[21] This is also why the plotted coefficients in Figure 3 can be essentially interpreted as the differences in rent sharing. The actual difference in income growth for coworking women in decile q is $\beta_0 + \beta_2^q$, but this will not differ substantially from β_2^q alone because $\hat{\beta}_0 \approx 0$.

sharing for coworking women are larger when their income constitutes a smaller share of household income: that is, in situations where the husband is the "breadwinner". Figure 4 presents estimates of Equation 3 separately for two groups of married women: in Panel (a), those whose income in the previous year was strictly less than half of total household income (they earned less than their husband), and in Panel (b), those whose income was half or more (they earn at least as much as their husband).

Figure 4: Rent Sharing Differences by Wife's Income Share

(a) Wife Income Share $< 50\%$ (b) Wife Income Share $\geq 50\%$



Note: Plotted coefficients are the β_2^q, the interaction of coworking with deciles of firm performance $q_{it}^{\Delta VA} \times CWC_{it}$.

We see that the rent sharing differences between coworking and non-coworking women are larger for women who earn less than their husbands than for those who earn as much or more. Rent sharing differences for women who earn at least half of the household income are smaller in magnitude and not statistically distinguishable from zero, though they likely are also not statistically distinguishable from the coefficients for those earning less than half due to power limitations. Still, the results from the estimation provide suggestive evidence that differences in rent sharing are larger for coworking wives in less equal marriages.

What might be the mechanism linking the spousal earnings gap to rent sharing differences? One possibility is that firms believe working couples somehow prioritize the career of the husband over that of the wife. If employers believe that coworking couples will prioritize the career of the husband, then they have an incentive to price discriminate less strongly against the husband to avoid a joint quit: if the husband is dissatisfied with his pay and quits, it is more likely that the wife will follow than vice versa.[22] These differences would be particularly stark for coworking women because the firm gets a much stronger signal of the relative income of the couple, observing the salaries of both partners as opposed to just one.

[22]It is worth emphasizing that the determining factor here is the firm's *beliefs*, which may or may not line up with the truth of how the couple makes career choices.

There are a variety of reasons couples might prioritize the career concerns of the husband over the wife. It could be that the distribution of job prospects is better for men than women, so that they have a more favorable distribution of potential earnings. If that were the case, even households that are *ex ante* egalitarian in that they weigh the welfare of the husband and wife equally would find it rational to make geographical and job-to-job mobility choices that prioritize the husband's career, simply because doing so results in higher total household income. However, this is far from the only potential explanation. Gendered social norms that men should be the primary "breadwinner" of the household may lead couples to prioritize the husband's career for non-pecuniary reasons (Bertrand et al., 2015).

Indeed, recent work in economics and sociology has found that when couples move to a new location, the earnings of husbands tend to grow faster than those of wives, suggesting that the husbands' earnings are a larger factor in joint location choices than wives' (Sorenson and Dahl, 2016; Jayachandran et al., 2023). I complement this analysis of differences in geographical mobility by analyzing differences in *job-to-job* mobility. In particular, I consider the empirical question of whether wives are actually more likely to follow their husbands away from an employer than vice versa. I begin with the set of coworking couples initially employed at the same plant, and consider events in which one spouse leaves the firm while the other initially stays behind. Then, I examine the impact of the gender of the stayiing spouse on probability that they also quit the plant in the 5 years after the initial leaving event. I estimate a linear probability model for leaving the plant on the gender of the staying spouse in the five years after the initial coworking relationship ended. To avoid bias stemming from cases where the wife quits her job in order to care for a new child, I focus only on events in which the initial spouse makes a job-to-job transition rather than quitting into nonemployment. Table 3 reports the results of this regression. The second column includes dummies for each of the 5 years after the initial event, and the third column includes various demographic controls.

We see that in the case where it was the husband who initially left the plant, the wife is about 4 percentage points more likely to subsequently quit than vice versa. Thus, it is empirically true in this sample that wives are more likely to follow their husbands, and employers may account for this asymmetry when setting wages.

Here I have presented some evidence that firm beliefs about gender differences in career concern can explain the observed gender differences in rent sharing. However, these differences could be consistent with a wide range of mechanisms, ranging from "neoclassical" differences in the distribution of potential earnings to gendered social norms about "breadwinner" status, or a mix between them, and distinguishing between them is ultimately an empirical question. Other potential factors could also be at play, such as gender bargaining

Table 3: Mobility After Coworking Spouse Leaves

	(1) Move b/se	(2) Move b/se	(3) Move b/se
Female Stayer	0.041***	0.041***	0.041***
	(0.004)	(0.004)	(0.004)
Yrs Since Move	No	Yes	Yes
Controls	No	No	Yes
R-Sq	0.002	0.051	0.090
Mean Dep. Var	.4	.4	.361
Observations	197,747	197,747	183,428

Note: Standard errors in parentheses, clustered at the couple level. Sample of initially coworking couples where one spouse leaves the plant, in the 5 years after the leave event. Controls for age fixed effects, education, location of both spouses, number of kids under 13, and year. Sample of female continuers in plants with at least 10 employees last year.

gaps,[23] These questions, while important, are beyond the scope of this paper, and I leave them to future research.

4.5 The Elasticity of Mobility to Wages

It is important to think more carefully about the exact mechanism by which mobility insures workers against the pass through of negative shocks. Consider a profit-maximizing firm deciding how much of a negative shock to pass through to a worker's wages. The primary tradeoff the firm faces is the direct cost savings of cutting wages versus the probability that the worker will quit due to dissatisfaction with the offered wage. If worker mobility was completely random and did not depend on wages at all, then a risk-neutral firm would gain nothing from treating workers who are less likely to quit differently: the wage offer would not affect the probability of quitting at all. Thus, what matters to the firm is not the *absolute* mobility of workers, but the *elasticity* of quits with respect to wages.

My estimates of mobility and rent sharing differences are informative about these elasticities. The relationship in Figure 2 can be thought of as a sort of "reduced form", in which firm performance determines the firm's offered wage schedule, which in turn determines workers'

[23] It may be the case that men bargain more aggressively with their employers, and are able to more credibly threaten to leave if they receive an unsatisfactory raise, consistent with recent papers such as Card et al. (2016), which finds that women generally capture a smaller share of match surplus than men at the same employer, potentially due to lower bargaining power, or Biasi and Sarsons (2022), which finds that the introduction of individual bargaining over teacher salaries in Wisconsin increases the gender wage gap, or Roussille (2022), which finds that even conditional on observable worker and job characteristics, women ask for lower salaries on average, suggesting less aggressive bargaining on their part.

mobility choices. We see that the slope of mobility with respect to firm performance is quite similar for coworking and non-coworking couples. The actual elasticity of quits to wages depends also on the "first stage": the effect of firm performance on offered wages. But we have exactly estimated this first stage in the previous section: coworking couples experience lower income growth when firms do poorly. Combining these results, the fact that coworking couples are equally sensitive to firm performance even though they receive *lower* income growth conditional on a level of firm performance means that they are necessarily *less* sensitive to income growth, consistent with the firm having greater monopsony power over them. To illustrate this in the data, I perform some back-of-the-envelope calculations using the binned scatterplots relating mobility to firm performance (Figure 2) and relating earnings growth to firm performance (Figure E5). In particular, for coworking and non-coworking women, I estimate the elasticity of mobility with respect to income growth implied by moving from the median level of firm performance to the lowest bin. We have that

$$\epsilon_{M,\Delta y} = \frac{\partial M_{it}/M_{it}}{\partial \Delta y_{it}/\Delta y_{it}}$$

Where the numerator is the percent (*not* percentage point) change in the probability of job-to-job mobility evaluated at the median bin and the denominator is the corresponding percent change in income growth. Beginning with coworking women, Figure moving from the median to the lowest bin of firm performance increases the probability of a job-to-job transition by about 1.5 percentage points, from a base of about 2.8 percentage points, a 54% increase. From Figure E5, income growth decreases by about 1.7 log points off a base of 2.5, a 68% decrease. The corresponding figures for non-coworking women are a 44% increase in mobility and a 9% decline in income growth. Thus, we have that

$$\epsilon^{CW}_{M,\Delta y} = \frac{.54}{-.68} = -0.8 \qquad \epsilon^{NCW}_{M,\Delta y} = \frac{.44}{-.09} = -4.9$$

So that coworking women are much less elastic to income changes than their non-coworking counterparts.

5 Robustness

The results I have presented so far highlight differences in rent sharing between coworking and non-coworking couples and are consistent with these differences originating from observable differences in worker mobility. However, coworking couples do not necessarily form at random, so it is worth considering the extent to which the preceding estimates might be influenced by various confounding factors. In this section I test the robustness of my results to two different kinds of confounding: selection bias stemming from focusing on stayers and from systematic differences in who becomes a coworking couple. I do not find evidence that either of these factors are responsible for the observed rent sharing differences in the data.

5.1 Selection into Staying

The estimates of rent sharing I have presented so far have been based on stayers, workers who remain at their employer. However, in this particular setting, where coworking and non-coworking couples differ in their mobility, focusing on stayers may result in selection bias. Suppose that for a given level of firm performance ΔVA, firms offer a range of raises Δy. Of course, especially low offers may induce workers to quit, in which case they will be excluded from my sample. But this means that the distribution of Δy for stayers reflects not the distribution of firm offers, but the distribution of *accepted* offers. As I have shown, coworking couples are less mobile, meaning they are uniformly more likely to accept an offer. Thus, even if firms offer all workers the same distribution of offers (firms do *not* price discriminate against coworking couples), it would appear that coworking couples face less generous rent sharing relationships simply because they are less selected: they are less likely to reject especially bad offers. Observed differences in the rent sharing relationship may reflect not only differences in firm behavior but also differences in worker behavior.

To address this concern, I consider a selection-corrected analogue of Equation (3) (Heckman, 1979). In particular, suppose the distribution of offered raises is given by

$$\Delta y_{it}^* = \beta_0 CWC_{it} + \sum_{q=1}^{9} (\beta_1^q d_{it}^q + \beta_2^q d_{it}^q \times CWC_{it}) + X_{it}'\delta + \varepsilon_{it}$$

However, we only observe the raise if the worker stays:

$$\Delta y_{it} = \Delta y_{it}^* \times \mathbb{1}\{S_{it}^* \geq 0\}$$

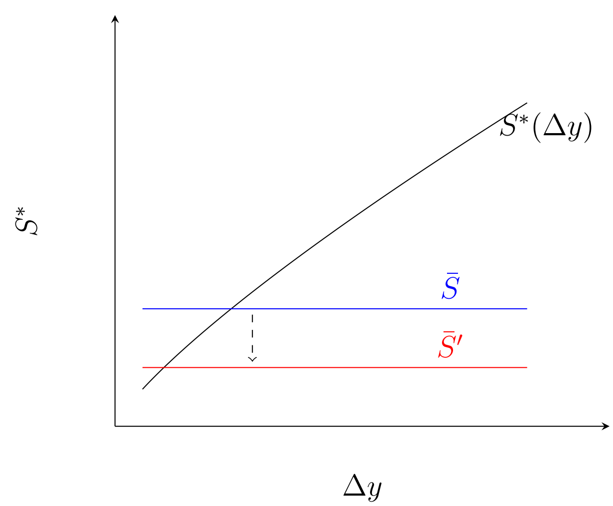
$$S_{it}^* = \beta_0 CWC_{it} + \sum_{q=1}^{9} (\beta_1^q d_{it}^q + \beta_2^q d_{it}^q \times CWC_{it}) + Z_{it}'\gamma + \nu_{it}$$

Where S_{it}^*, the latent utility associated with staying, itself depends on the offered raise implied by the firm's performance, as well as a set of observables Z_{it} which may differ from those determining the offer distribution.

Credible identification of this model requires finding instruments that affect the decision to move but not the distribution of offers, *conditional* on the firm's productivity shock. I include two sets of instruments in the selection equation. First, I include indicators for mass layoff and mass "churn" events, corresponding to very high levels of separations at the plant level. In line with the literature, I define a plant as experiencing a mass layoff event in a year if its total employment decreased by more than 30% that year, an indicator of large net outflows. I also consider mass "churn" events where more than 30% of employees in the previous year separate from the plant this year, regardless of the actual change in firm size, an indicator of large gross outflows. The intuition here is that workers who separate from the firm during these high separation periods are much less likely to be doing so voluntarily: they are separating for reasons other than dissatisfaction with their offered raise.

The second set of instruments are changes in the outside option for workers. In particular, for each worker-year, I compute the employment and earnings growth in their gender-industry-county cell, leaving out their own employer, to capture variation in the availability and quality of outside options. I illustrate the idea in Figure 5.

Figure 5: Outside Option Variation



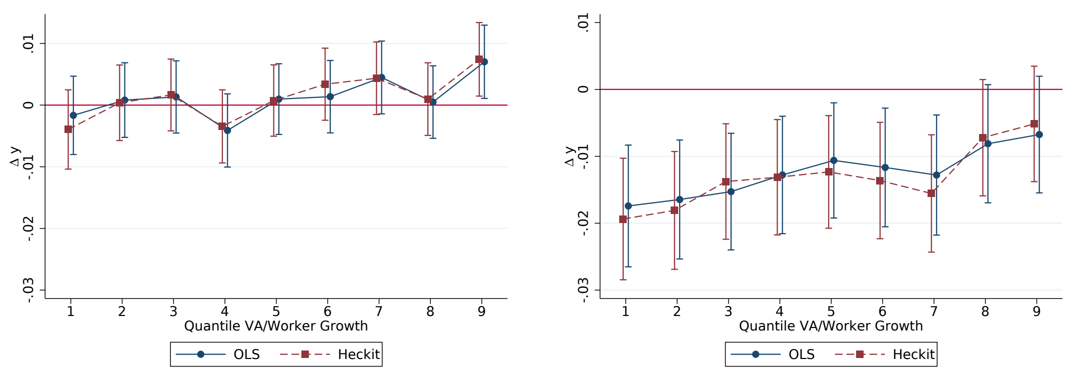
The latent utility of staying, $S^*(\Delta y)$, depends on the offered raise Δy. The worker stays so long as this utility is above some threshold $\bar{S}$, which represents the worker's outside option (or their beliefs about it). Then, variation in this outside option will trace out the left tail of $S^*(\Delta y)$. Since ΔVA represents idiosyncratic variations in firm performance residualized of industry and time effects, these should be orthogonal by construction to the evolution of the worker's outside option.[24]

[24]It is worth noting that this mechanism depends on assumptions about the wage bargaining process: incumbent firms must make take-it-or-leave-it offers to workers. If workers are able to bargain with their employers, then improvements in the outside option can lead to higher wages even for stayers. However, the results are nearly identical if I omit these variables and estimating the Heckit model with only the mass layoff and churn as excluded instruments.

I estimate this model separately for men and women using maximum likelihood. In Figure 6 I plot the estimates $\hat{\beta}_2^q$ of the interaction between deciles of firm performance and coworking status, with men in Panel (a) and women in Panel (b). The selection-corrected estimates are extremely similar to the OLS. For men, there are still largely no differences in rent sharing between coworking and non-coworking couples, while coworking women have substantially lower income growth when the firm is doing poorly than their non-coworking counterparts. Thus, the finding that coworking women experience systematically less generous rent sharing schedules is robust to accounting for the potential selection bias introduced by focusing on stayers.

Figure 6: Rent Sharing Estimates by Gender, Selection Corrected

(a) Men (b) Women



Note: Plotted coefficients are the β_2^q, the interaction of coworking with deciles of firm performance $q_{it}^{\Delta VA} \times CWC_{it}$.

5.2 Selection into Coworking

Alternatively, selection bias could also arise from the fact that coworking couples might not form at random. If the kinds of individuals who would end up coworking with their spouse are less productive, then the observed differences in income growth for these individuals may be the result not of firm monopsony power but rather a lower marginal product of labor. In this section I present robustness exercises which suggest that this form of selection does not account for the observed differences in rent sharing. In particular, I consider two potential sources of selection bias: persistent differences in individual productivity of the sort that would be captured in a individual fixed effect, and differences in match-specific productivity arising from the job search and matching process.

First, I consider persistent individual productivity differences. If women who are more likely to work with their spouses have systematically lower income growth due to, for example, weaker labor force attachment or a lesser propensity to accumulate human capital, then the estimated rent sharing relationships could reflect not only differences in monopsony power but also differences in productivity. I argue that such systematic differences are unlikely to explain the observed results for two reasons. First, differences in productivity should be reflected not only in income *growth* but also income *levels*. In Figure 1, we saw that while coworking couples are somewhat overrepresented at the bottom and top of the income distribution, they are quite common throughout it: this is not a phenomenon that is observed solely for low-income women. To further address this concern, I focus on a subgroup of coworking couples: those that met at the workplace. In particular, I consider the income growth of eventually-married women *prior* to marriage, and compare the income growth of those who eventually end up marrying a coworker versus those who do not. Table 4 presents the results of a regression of income growth on an indicator for whether a given female worker married a coworker, for the sample of eventually-married women pre-marriage. We see that if anything, women who eventually end up marrying a coworker had *higher* income growth prior to marriage, meaning that they are not systematically and persistently less productive.

Table 4: Selection: Married a Coworker

	(1)	(2)	(3)
	Δy	Δy	Δy
	b/se	b/se	b/se
Married Coworker	0.009***	0.007***	0.010***
	(0.001)	(0.001)	(0.002)
Controls	No	Yes	Yes
Plant-Year FE	No	No	Yes
R-Sq	0.000	0.017	0.285
Mean Dep. Var	.0741	.0741	.0771
Observations	846,605	846,436	581,281

Note: Standard errors in parentheses, clustered at the couple level. Controls for age fixed effects, education, location of both spouses, year, number of kids under 13, and plant fixed effects. Sample of pre-marriage female continuers aged 25-60.

A more subtle kind of selection bias might arise from systematic differences in match quality for coworking couples. If coworking women tend to remain in jobs to which they are less well matched because they prefer to work with their spouse, then they may be less productive and hence experience lower earnings growth. To address this concern, I focus on a subset of coworking women who are less likely to be subject to this effect: those who became coworking couples because their spouses joined them at *their* workplace. I focus on the sample of these female "joined-by-spouse" workers, and compare their income growth to that of their married female peers at the same workplace using a two way fixed effect difference-in-difference specification:

$$\Delta y_{it} = \alpha_i + \gamma_t + \beta \times \text{Joined by Spouse}_{it} + X_{it}'\delta + \varepsilon_{it}$$

Where Joined by Spouse_{it} is an indicator for observations of these women after their spouse has joined them.

Table 5: Income Growth, Coworking Women Joined by Spouse

	(1) Δy_{it} b/se	(2) Δy_{it} b/se
Joined by Spouse	-0.012***	-0.006***
	(0.002)	(0.002)
Controls	No	Yes
Individual FE	Yes	Yes
Time FE	Yes	Yes
R-Sq	0.171	0.224
Mean Dep. Var	.0369	.0369
Observations	3,438,548	3,438,451

Note: Standard errors in parentheses, clustered at the couple level. Sample of female continuers joined by their spouses and non-coworking female continuers in plants with at least 10 employees last year.

Table 5 reports the results of this regression. We see that even for women who end up in a coworking because their spouse joins them at their current workplace, income growth is significantly lower after becoming a coworking couple, meaning that for this subgroup of coworking couples, differences in income growth are not being driven entirely by differences in job match quality.

6 Differences in Income Growth and Risk

I have shown that women in coworking couples experience very different rent sharing relationships with their employers. Price discrimination by employers on the basis of observable differences in mobility materially affects firm rent sharing behavior. But what might be the consequences of these rent sharing differences for the welfare of workers? To answer this question in the current setting, I now present a comprehensive analysis of differences in the dynamics of household income for coworking and non-coworking couples. In particular, I document substantial differences in the first two moments of the distribution of household income growth: coworking couples experience 23% lower average annual household income growth, and about 57% higher income risk. In benchmark models of household behavior, the growth rate and risk of the income process are the primary determinants of welfare, meaning that coworking couples face, *ceteris paribus*, a less desirable income process. Therefore, the goal of this section is to demonstrate that the differences in rent sharing documented so far are not a mere curiosity, but can have material effects on worker welfare.

6.1 Coworking Couples Have Lower Income Growth

To quantify the differences in household income growth Δy_{it}^{hh} for coworking versus non-coworking couples, I run regressions of the form

$$\Delta y_{it}^{hh} = \beta CWC_{it} + X_{it}'\delta + \varepsilon_{it} \tag{4}$$

Where CWC_{it} is an indicator for couple i working at the same plant in year t, and X_{it} is a vector of controls, up to a full set of plant-by-year fixed effects.[25] β thus represents the average difference in household income growth when comparing coworking and non-coworking employees in the same plant and year. I limit the sample to individual continuers, workers who were employed at the same plant this year and last year, to maintain consistency with the rent sharing estimates to follow, employed in plants with at least 10 workers last year. Table 6 reports the results of this regression.

Column (4), which controls for plant-year fixed effects, is the preferred specification, but we see that difference in income growth for coworking couples remains very similar when including an expanding set of controls. Coworking couples have 0.7 log points lower income growth even when compared to their non-CWC counterparts in the *same* plant and year. Given an average household income growth of 3.1 log points per year in the sample, this amounts to 23% lower income growth for coworking couples.

By what process are these large differences in income growth generated? The fact that these effects persist even when controlling for a full set of plant-by-year fixed effects rules out sorting of coworking couples to firms with lower average income growth: coworking couples receive on average smaller raises than their peers at the same employer. Does this difference in average rank reflect slightly lower income growth in every year, or a lower chance of large one-time raises? To answer this, I rank married continuers into deciles of household income growth within a plant-year, and compare the distributions of these ranks for coworking and

[25] In particular, I control for education, county, age fixed effects for both spouses, year fixed effects, the number of children under 13, and the worker's decile of income within their plant, to control for within-workplace rank effects. I also include either plant or plant-by-year fixed effects, effectively comparing coworking couples to their non-CWC peers.

Table 6: Household Income Growth by Coworking

	(1)	(2)	(3)	(4)
	Δy^{hh}	Δy^{hh}	Δy^{hh}	Δy^{hh}
	b/se	b/se	b/se	b/se
Coworking	-0.006***	-0.007***	-0.007***	-0.007***
	(0.000)	(0.000)	(0.000)	(0.000)
Controls	No	Yes	Yes	Yes
Plant FE	No	No	Yes	No
Plant-Year FE	No	No	No	Yes
R-Sq	0.000	0.019	0.034	0.127
Mean Dep. Var	.031	.031	.031	.031
Observations	11,580,681	11,577,439	11,570,327	11,506,261

Note: Standard errors in parentheses, clustered at the couple level. Controls for age fixed effects, education, location of both spouses, year, within-firm income decile, number of kids under 13, and plant fixed effects. Sample of continuers aged 25-60 at plants with at least 10 employees last year.

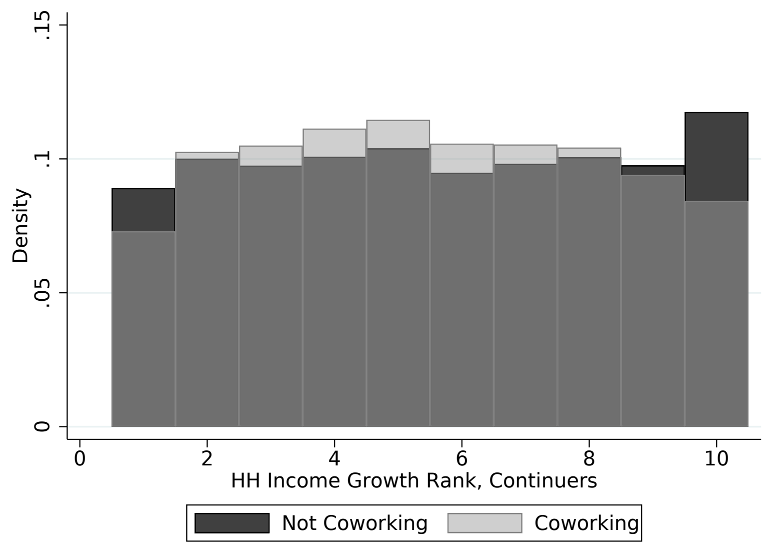
non-coworking couples. Figure 7 plots the results.

The most visible difference in the distribution of ranks is that coworking couples are underrepresented in the top decile of income growth, meaning that they are less likely to receive large raises. They are also somewhat less likely to be in the lowest decile, with the difference being made up by modestly higher representation in the lower half of the distribution. Thus, the differences in income growth seem to be driven by coworking couples being less likely to receive large raises.[26]

I have shown that coworking couples experience significantly lower income growth. But, is this difference the same across genders? To answer this I run again the regression specified in Equation (4), but separately for men and women, using *individual* rather than household income growth as the dependent variable. Table 7 presents the results of these regressions with the full set of plant-by-year fixed effects. Column (1) is the sample of men, while Column (2) is the sample of women. We see that while both coworking men and women have significantly lower income growth, the effect is much larger for women, who have 0.6 log points lower growth on average, compared to just 0.1 log points for men. Thus, the differences in household income growth for coworking couples are driven primarily by lower growth for the wife, a fact consistent with the differences in rent sharing documented in Section 4.

[26]This would be consistent also with coworking couples being less likely to be promoted. Part of the reason this may be the case is that while most workplaces permit relationships between employees, it is common for relationships between managers and subordinates to be forbidden, which may make it more difficult for coworking couples to receive promotions if it would result in one becoming the other's direct supervisor.

Figure 7: Within-Plant Household Income Growth Ranks



Note: Histograms of within-plant-year deciles of household income growth for continuers. Sample of plants with at least 10 continuers.

Table 7: Individual Income Growth by Coworking

	(1) Men b/se	(2) Women b/se
Coworking	-0.001***	-0.006***
	(0.000)	(0.001)
Controls	Yes	Yes
Plant FE	No	No
Plant-Year FE	Yes	Yes
R-Sq	0.176	0.172
Mean Dep. Var	.0285	.037
Observations	5,818,589	5,451,262

Note: Standard errors in parentheses, clustered at the couple level. Controls for age fixed effects, education, location of both spouses, year, within-firm income decile, number of kids under 13, and plant fixed effects. Sample of married male continuers aged 25-60 at plants with at least 10 employees last year.

The finding that coworking couples have on average lower income *growth rates* implies that over time their income levels should fall behind those of their non-coworking counterparts. However, in Table 1, I showed that coworking couples appear to have, on average, quite similar *levels* of household income. It turns out that this similarity is the result of differences in the age compositions of coworking and non-coworking couples. As seen in Appendix Figure E6, coworking couples skew somewhat older, meaning that they are over-represented near the life cycle income peak relative to non-coworking couples (Appendix Figure E7).

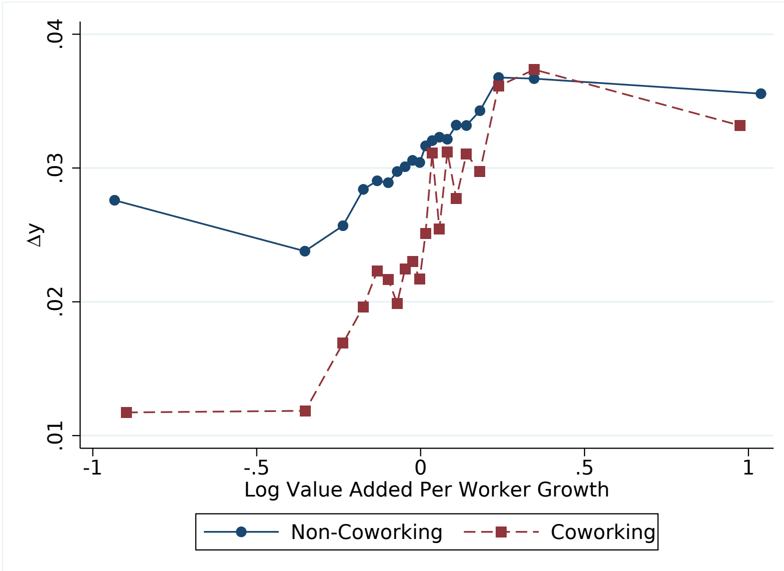
6.2 Coworking Couples Have Higher Income Risk

From Table 1, we see that coworking couples have higher variances of both individual and household income growth compared to non-coworking couples. However, in addition to higher individual risk, there is another factor which may lead to differences in household income risk for coworking couples: a higher *correlation* between their individual incomes. To the extent that firms transmit idiosyncratic productivity shocks to their workers' earnings, the individual incomes of coworking couples will be more strongly correlated than those of non-coworking couples, since they will be subject to a common firm-level shock. Since household income is the sum of each spouse's individual income, this will raise the variance of household income. This covariance effect is clearly visible if we examine the response of *household* income to firm performance. Figure 8 plots a binned scatterplot of average household income growth against firm performance for coworking (dashed red square) and non-coworking (solid blue circle) couples.

There is a clear asymmetry in the rent-sharing relationship. When the firm does poorly ($\Delta VA < 0$), coworking couples experience much lower income growth. However, when the firm does well ($\Delta VA > 0$), coworking couples experience as much income growth as non-CWC. At the left tail of the distribution, the differences are quite large: coworking couples have more than a log point lower income growth in the bottom two ventiles of the firm performance distribution. This picture looks quite different to the individual rent sharing schedules estimated in Figure 3: the slope of the pass-through for coworking couples is much steeper at the household level than the individual level, reflecting the greater covariance of the individual shocks.

This means that even if there were no difference in the riskiness of each spouse's individual income, coworking couples will have higher household income risk simply because their incomes are more correlated. In the context of rent sharing, this means that even if all employees have the same pass-through rate of firm shocks, the *household* income risk of

Figure 8: Rent Sharing, Household Income Growth



Note: The dependent variable is household income growth. Sample of individual continuers.

coworking couples would be higher because they are hit twice by the same shock. The goal of this section, then is not only to document differences in income risk, but quantify how much of these differences stem from the covariance effect, which is purely mechanical, and how much comes from differences in the individual riskiness of each spouse, which must stem from differential choices by workers or treatment by firms.

To do this, I first need a conceptual measure of household income risk. I choose the time-t *conditional* variance of household income growth, $Var_t(\Delta y_{it+1}^{hh})$, where the conditioning is on the household's information set. This measure corresponds most closely to the concept of uncertainty actually faced by households: it does not include predictable variations in income growth stemming from, for example, the receipt of a one-time bonus in the previous year. This measure also permits a simple and intuitive decomposition of household income risk into components corresponding to the variance of each spouse's individual income and the covariance between them, shedding light on the relative importance of individual differences and the covariance effect.

The decomposition is as follows. Begin with the fact that household i's income (in levels) is simply the sum of the spouses' individual income (let spouse 1 be the wife): $Y_{it}^{hh} = Y_{it}^{1} + Y_{it}^{2}$.

Then, it can be shown that household income *growth* is:[27]

$$\Delta y_{it+1}^{hh} \approx \omega_{it}\Delta y_{it+1}^{1} + (1-\omega_{it})\Delta y_{it+1}^{2}$$

Where $\omega_{it} = Y_{it}^1/Y_{it}^{hh}$ is the wife's share of household income last year, and the approximation arises from substituting log differences for growth rates. In other words, household income growth is simply the weighted average of individual income growth, where the weights are each spouse's share of income in the previous year. Then, since the ω_{it} are known at time t, the conditional variance of household income growth is given by:

$$Var_t(\Delta y_{it+1}^{hh}) = \underbrace{\omega_{it}^2 Var_t(\Delta y_{it+1}^{1})}_{\text{Wife's Variance Term}} + \underbrace{(1-\omega_{it})^2 Var_t(\Delta y_{it+1}^{2})}_{\text{Husband's Variance Term}} + \underbrace{2\omega_{it}(1-\omega_{it})Cov_t(\Delta y_{it+1}^{1}, \Delta y_{it+1}^{2})}_{\text{Covariance Term}} \tag{5}$$

That is, the sum of three terms corresponding to the individual income risk of each spouse and the covariance between them.

While intuitive, this decomposition has the issue that conditional variances are not directly observable: the econometrician does not know the household's information set in year t, so it is not possible to determine how much of the observed dispersion in income growth was known to the household from the data alone. I overcome this issue by imposing further structure on the individual income processes. In particular, I assume that the log income of spouse s can be described by the following process:

$$y_{it}^{s*} = X_{ist}'\delta^s + p_{it}^s + \varepsilon_{it}^s \quad p_{it}^s = p_{it-1}^s + \zeta_{it}^s$$

That is, the sum of observable factors X_{ist}, a persistent unit root term p_{it}^s with innovation ζ_{it}^s, and an idiosyncratic shock ε_{it}^s. I assume that the permanent and transitory innovations are uncorrelated for an individual, but may be correlated with the corresponding innovations for their spouse:

$$\begin{pmatrix}\zeta_{it}^1\\ \zeta_{it}^2\end{pmatrix} \sim \begin{pmatrix}0\\0\end{pmatrix}, \begin{pmatrix}\sigma_{1\zeta}^2 & \\ \sigma_{12\zeta} & \sigma_{2\zeta}^2\end{pmatrix} \quad \begin{pmatrix}\varepsilon_{it}^1\\ \varepsilon_{it}^2\end{pmatrix} \sim \begin{pmatrix}0\\0\end{pmatrix}, \begin{pmatrix}\sigma_{1\varepsilon}^2 & \\ \sigma_{12\varepsilon} & \sigma_{2\varepsilon}^2\end{pmatrix}$$

Given this structure, the conditional variance and covariance terms in Equation (5) are functions only of the variances and covariances of the permanent and transitory shocks:

$$Var_t(\Delta y_{it+1}^{s}) = \sigma_{s\zeta}^2 + \sigma_{s\varepsilon}^2 \quad Cov_t(\Delta y_{it+1}^{1}, \Delta y_{it+1}^{2}) = \sigma_{12\zeta} + \sigma_{12\varepsilon}$$

[27]See Appendix D.1 for details.

Given estimates of the income process parameters $(\sigma^2_{1\zeta}, \sigma^2_{1\varepsilon}, \sigma^2_{2\zeta}, \sigma^2_{2\varepsilon}, \sigma_{12\zeta}, \sigma_{12\varepsilon})$ and the income shares ω_{it} for a household, it is possible to obtain an estimate of each term of Equation (5), and by adding them, an estimate of the conditional variance of household income growth for each household in every year. The ω_{it} are observed and can be calculated directly in the data. To estimate the parameters of the income process, I follow the extensive literature on estimating income processes using covariance restrictions.[28] In particular, I first residualize y^{s*}_{it} on a set of observables X_{ist} separately for each spouse.[29] I then take first differences to obtain

$$y^s_{it} = y^{s*}_{it} - X'_{ist}\hat{\delta}^s = p^s_{it} + \varepsilon^s_{it} \implies \Delta y^s_{it} = \zeta^s_{it} + \Delta\varepsilon^s_{it}$$

Then, the parameters of interest are identified by the *unconditional* variance, cross-covariances, autocovariances, and cross-autocovariances of Δy^s_{it}:

$$\begin{aligned}
Var(\Delta y^s_{it}) &= \sigma^2_{s\zeta} + 2\sigma^2_{s\varepsilon} \\
Cov(\Delta y^s_{it}, \Delta y^s_{it-1}) &= -\sigma^2_{s\varepsilon} \\
Cov(\Delta y^1_{it}, \Delta y^2_{it}) &= \sigma_{12\zeta} + 2\sigma_{12\varepsilon} \\
Cov(\Delta y^1_{it}, \Delta y^2_{it-1}) = Cov(\Delta y^1_{it-1}, \Delta y^2_{it}) &= -\sigma_{12\varepsilon}
\end{aligned}$$

I estimate the parameters of the income process using GMM *separately* for coworking and non-coworking couples. Thus, in my results, differences in income risk can arise from:

1. Differences between coworking and non-coworking couples in the variance of permanent and/or transitory innovations for either spouse.

2. Differences between coworking and non-coworking couples in the covariance of permanent and/or transitory innovations between spouses.

3. Differences in the wife's share of household income.[30]

For this exercise, I take as my sample dual-continuers, couple-years where both spouses remain at their previous employer. I also make several additional sample restrictions. First, I keep observations where both spouses have only one employer, to focus on full-time workers. I also use the stockholder registry to identify individuals who own the business they are employed at. The split between labor and business income is significantly less clear for these

[28] See, for example, Hall and Mishkin (1982) or Blundell et al. (2008).

[29] I residualize on age, education, location, number of children, and year.

[30] In particular, I show in Appendix B.3 that coworking couples are more assorted on average, meaning that the wife's share of household income is relatively higher. This will imply a larger covariance term independent of the parameters of the income process, as $\omega_{it}(1 - \omega_{it})$ is maximized when $\omega = 1/2$.

owners, so I exclude them. The stockholder registry data begins in 2004, so the time range for this exercise spans 2004-2014.

Table 8 reports the income process estimates. We see that the variances of the permanent and transitory components of individual income, as well as the covariance between innovations, are all larger for coworking couples compared to non, suggesting a role for both higher individual variances and covariances in explaining the higher overall income risk.

Table 8: Income Process Estimates

	(1)	(2)
	b/se	b/se
$\sigma^2_{1\zeta}$	0.0504***	0.0387***
(Var perm shock, wife)	(0.0021)	(0.0005)
$\sigma^2_{1\varepsilon}$	0.0061***	0.0035***
(Var trans shock, wife)	(0.0008)	(0.0002)
$\sigma^2_{2\zeta}$	0.0269***	0.0248***
(Var perm shock, husband)	(0.0017)	(0.0005)
$\sigma^2_{2\varepsilon}$	0.0077***	0.0043***
(Var trans shock, husband)	(0.0009)	(0.0002)
$\sigma_{12\zeta}$	0.0044***	0.0001
(Cov perm shock)	(0.0006)	(0.0001)
$\sigma_{12\varepsilon}$	0.0005*	0.0002***
(Cov trans shock)	(0.0003)	(0.0000)
Group	CWC	Non-CWC
Observations	72,806	904,969

Note: Standard errors in parentheses, clustered at the couple level. Estimation via two-step GMM.

To quantify the average differences in income risk in my sample, I first compute the actual income shares ω_{it}, and construct the corresponding variance and covariance terms using these shares and the estimated income processes for each couple-year. I then compute the averages of each term for coworking and non-coworking couples, and report these averages, as well as the average conditional variance, which is simply the sum of the terms. Table 9 contains the results of this exercise.

The first column of the table gives the average conditional variance of household income growth for coworking and non-coworking couples. We see that coworking couples have significantly higher average conditional variances, at 0.019 vs 0.012 for non-coworking couples, or about 57% higher. Higher individual variances and higher covariance both play a role in this difference. The last row of the table measures what fraction of the difference in total variance stems from differences in each component. Higher income risk for coworking wives

Table 9: Conditional Variance Decomposition

$$Var_t(\Delta y^{hh}_{it+1}) = \underbrace{\omega^2_{it} Var_t(\Delta y^1_{it+1})}_{\text{Wife's Variance Term}} + \underbrace{(1-\omega_{it})^2 Var_t(\Delta y^2_{it+1})}_{\text{Husband's Variance Term}} + \underbrace{2\omega_{it}(1-\omega_{it}) Cov_t(\Delta y^1_{it+1}, \Delta y^2_{it+1})}_{\text{Covariance Term}}$$

	Cond Var	Wife Var Term	Husb Var Term	Cov Term
Coworking	0.0194	0.0106	0.0065	0.0023
Non-Coworking	0.0123	0.0072	0.0050	0.0001
Difference	0.0070	0.0034	0.0015	0.0021
Frac Explained	1	0.4797	0.2160	0.3042

Note: Table reports the sample averages of the estimated conditional variance and each decomposition term for dual-continuer coworking and non-coworking couples.

is the most important factor, explaining 48% of the difference. A higher covariance is next, explaining 30%, and higher risk for husbands explains 22%.

In summary, I find that coworking couples do indeed face much higher income risk, as measured by the conditional variance of income growth. This difference arises both because coworking spouses have higher individual income risk, with larger differences for wives than husbands, as well as a much larger covariance between their individual income growths, as would be expected if firms pass through idiosyncratic shocks. Thus, I show that while the covariance effect is indeed a strong contributor to the dynamics of household income growth, it is not the only factor leading to greater risk: consistent with the finding of large rent sharing differences for coworking women, the largest contributor to the differences in risk is the individual riskiness of the wife. This fact, together with the less generous rent sharing of coworking couples, accounts for the asymmetric pattern in household rent sharing observed in Figure 8.

7 Linking Income Dynamics and Rent Sharing

So far, I have shown that coworking couples experience different rent sharing patterns than their non-coworking counterparts. These patterns are qualitatively consistent with the observed differences in income growth and risk for coworking couples documented in Section 6: the fact that these couples face a greater downside when the firm does poorly but no compensating upside when the firm does well means they will have lower income growth, whereas the fact that this gap closes across the productivity distribution means their income growth covaries more strongly with firm performance, increasing income risk. But, how much of the differences in household income dynamics can actually be accounted for by these differences in rent sharing?

To answer this, I perform the following exercise. I ask: how much of the gaps in income growth and risk can be explained only by variation in firm performance and differences in rent sharing conditional on performance? Consider again Equation (3):

$$\Delta y_{it} = \beta_0 CWC_{it} + \sum_{q=1}^{9}(\beta_1^q d_{it}^q + \beta_2^q d_{it}^q \times CWC_{it}) + X_{it}'\delta + \varepsilon_{it}$$

I predict individual income growth separately for each spouse using only the terms corresponding to firm performance:

$$\widehat{\Delta y^s} = \beta_0 CWC_{it} + \sum_{q}(\hat{\beta}_1^q q_{it}^{\Delta VA} + \hat{\beta}_2^q q_{it}^{\Delta VA} \times CWC_{it})$$

Then, to go from individual to household income, I use the fact that household income growth is the weighted average of the spouses' individual income growth:

$$\widehat{\Delta y^{hh}} = \omega_{t-1}\widehat{\Delta y^1} + (1-\omega_{t-1})\widehat{\Delta y^2}$$

Where ω_{t-1} is, again, the wife's share of household income last year. The result of this is a predicted income growth for each household-year based only on the performance of their employer(s) and whether they are a coworking couple. Because of the estimated shape of the rent sharing relationships, $\widehat{\Delta y^{hh}}$ will have a lower average and higher dispersion for coworking couples.[31] Then, to quantify how much of the observed differences in growth and risk can be explained by differences in rent sharing, I compute $\widehat{\Delta y^{hh}}$ for each household in the sample and calculate:

$$\frac{E[\widehat{\Delta y^{hh}}|CWC=1] - E[\widehat{\Delta y^{hh}}|CWC=0]}{E[\Delta y^{hh}|CWC=1] - E[\Delta y^{hh}|CWC=0]}$$

and

$$\frac{sd(\widehat{\Delta y^{hh}}|CWC=1) - sd(\widehat{\Delta y^{hh}}|CWC=0)}{sd(\Delta y^{hh}|CWC=1) - sd(\Delta y^{hh}|CWC=0)}$$

That is, what fraction of the observed differences in the mean and standard deviation of household income growth can be predicted from the rent sharing relationship alone?

I find that rent sharing is quite important: differences in rent sharing alone can account for **44%** of the differences in income growth and **10%** of the differences in income risk. That

[31] Assuming, of course, that the *distribution* of firm performance is similar for these two groups, that is, that there are not significant differences in the sorting of workers to firms on the basis of productivity. The fact that the quantile bins of productivity in Figure 3 are quite similar for coworking and non-coworking couples shows that this is indeed the case.

the estimated rent sharing schedules can explain a larger share of the difference in income growth than risk is consistent with the fact that the individual estimates do not display quite as stark a difference in linear steepness as the household relationship plotted in Figure 8. Coworking women have lower income growth across the distribution of firm performance, and this gap only decreases a little as we move from the first to the ninth decile. Nevertheless, it is clear that differences in rent sharing are important for explaining the differences in household income dynamics for coworking couples. Thus, not only do I find support for the theoretical prediction that firms account for observable differences in the average mobility of workers when setting rent sharing schedules, I also find that this exercise of monopsony power creates noticeable differences in household income dynamics.

7.1 Welfare

I have shown that coworking couples face significantly lower household income growth and higher risk than their non-coworking counterparts. This rules out the possibility that the observed income dynamics represent a tradeoff between risk and return for these households, in which they accept lower income growth in exchange for more certainty, or vice versa. What, then, do these differences imply about household welfare for coworking couples? It is useful to think about welfare under two polar cases: a completely frictional labor market and a completely frictionless one.

Consider first a completely frictional labor market, in which workers have no ability to switch employers. Suppose also that workers are risk averse and value work only for the income it provides. Then, the fact that coworking couples have lower income growth and higher risk suggests that they must have lower welfare, as they are subject to greater income uncertainty with no reward in the form of higher expected growth–indeed, they expect lower growth.

Suppose instead that the labor market is frictionless, so that workers may choose their employer freely. Then, the fact that we observe coworking couples despite the fact that they experience less favorable income dynamics on average must mean that they are obtaining some benefit from these relationships. In fact, it must be the case that they are exactly compensated for the welfare losses of a riskier and less generous income process: the implied differences in welfare can be interpreted as the willingness-to-pay for the amenity of sharing a workplace with your spouse.[32]

[32] Of course, it is possible that couples differ in their valuation of this amenity–given that I estimate differences for the couples who choose to work together, what I actually observe is the average willingness to pay for the couples who choose to cowork, which in the frictionless case will be those with the highest valuations.

In either case, it is useful to compute the implied welfare differences for coworking couples if all they cared about was income growth and risk. In the frictional case this would measure the differences in welfare for these households, whereas in the frictionless case it would measure the willingness to pay for the amenity of working together. In reality, job choice reflects a mix of frictions and choice, so the truth will be somewhere in between. To get a rough estimate of the welfare implications, I consider a simple exercise in the spirit of Lucas (1987). Consider an infinitely lived household that has CRRA utility in consumption

$$U = E\sum_{t=0}^{\infty}\beta^t \frac{c_t^{1-\gamma}}{1-\gamma}$$

And faces a lognormal consumption process

$$c_t = (1+g)e^{-\sigma_z^2/2}e^{z_t} \quad z_t \sim N(0,\sigma_z^2)$$

So that g is the average growth rate of consumption, and σ_z^2 represents risk. Suppose this household is faced with two possible consumption streams: a "coworking" and "non-coworking" stream that differ in terms of growth rates (g^{cw}, g^{nc}) and variances $(\sigma_{cw}^2, \sigma_{nc}^2)$. Then, the welfare difference betweeen these two consumption streams can be quantified as the consumption equivalent λ such that:

$$E\sum_{t=0}^{\infty}\beta^t \frac{\left((1+\lambda)(1+g^{cw})e^{-\sigma_{cw}^2/2}e^{z_t^{cw}}\right)^{1-\gamma}}{1-\gamma} = E\sum_{t=0}^{\infty}\beta^t \frac{\left((1+g^{nc})e^{-\sigma_{nc}^2/2}e^{z_t^{nc}}\right)^{1-\gamma}}{1-\gamma}$$

That is, λ is the percent increase in consumption that would be required to make the household indifferent between coworking and not. It is easy to show that under these assumptions, λ is approximated by:[33]

$$\lambda \approx (g^{nc} - g^{cw}) + \frac{1}{2}\gamma(\sigma_{cw}^2 - \sigma_{nc}^2) \tag{6}$$

Unsurprisingly, the welfare difference is larger when the coworking consumption stream has lower relative growth or higher risk. The more risk averse the household is, as measured by γ, the more important differences in risk become. From Table 6, I estimateed that $g^{nc} - g^{cw} = 0.007$, and from Table 9 that $\sigma_{cw}^2 - \sigma_{nc}^2 = 0.007115$. In choosing γ, I follow Guiso et al. (2005), who perform a similar exercise to quantify the value of firm-provided insurance from productivity risk, and set $\gamma = 3$, implying that the welfare cost of being in a coworking couple is $\boldsymbol{\lambda = 1.78\%}$ of consumption annually, a substantial figure.[34]

[33] See Appendix D.2 for details.

[34] Note that here I am quantifying the welfare effects of the full difference in income dynamics for coworking couples. Focusing instead on the differences explained by rent sharing will somewhat reduce these figures,

Are frictions or amenities a more plausible explanation for these differences? It is easy to think of various amenities that coworking couples might enjoy that make them less likely to separate from their job: for example, reduced commuting costs from carpooling, the ability to smooth shocks to the marginal utility of home production (e.g. childcare demands) by covering for each other's tasks, or spending more time together. Potential frictions are somewhat more subtle. The mere presence of frictions in the labor market is not sufficient to generate welfare differences: coworking couples would have to face *greater* frictions to mobility. However, one potential example would be reduced networking opportunities for outside hiring. Because coworking couples share a workplace, they also share a common network of other coworkers. This means that one spouse may be less able to benefit from referrals and connections from the other's colleagues, reducing the effectiveness of the social network as a labor market matching technology. Thus, while amenities likely explain a large part of the welfare difference, there is also a potential role for frictions in the labor market.

8 Conclusion

In this paper I present novel evidence of the tight connection between monopsony power and rent sharing between firms and their workers. In an environment where workers vary in how easily they can move between employers, and these differences are (partially) observable, theory predicts that firms should take advantage of these differences to offer different rent sharing relationships to observably different workers. I study this prediction in the context of coworking couples in Norway, married couples who share a workplace, presumably in part because they value the amenity of working together. Consistent with the theory, I find that coworking couples are significantly less mobile than their non-coworking counterparts, and that firms take advantage of this lower mobility by engaging in less generous rent sharing relationships with them, with coworking women in particular experiencing lower income growth conditional on firm performance.

These differences in rent sharing are large enough to induce sizable differences in household income dynamics for coworking couples, who face significantly lower household income growth and higher risk on average, amounting in welfare terms to about 1.8% of consumption per year. This figure may reflect either genuine differences in realized utility for coworking couples or estimate the willingness to pay for the amenity of working with one's spouse, depending on the degree of frictions in the labor market.

One key finding is that coworking women in particular drive the observed differences in both rent sharing and income dynamics, even though both coworking men and women

as not all of the differences in growth and risk result from rent sharing alone.

exhibit lower mobility. I present evidence that these gender differences may reflect employer beliefs about the relative importance placed on the husband's versus the wife's career within the household, providing additional evidence that gender roles matter when considering monopsony power in the labor market.

Ultimately, this paper makes the case that worker mobility is an important and welfare-relevant source of insurance against idiosyncratic firm risk, important enough that firms take differences in mobility into account when setting wages. It provides evidence that there may be important differences in rent sharing even within a firm, and that substantial progress can be made in understanding these differences along observable lines by providing a simple theoretical framework linking rent sharing to mobility. This paper also takes advantage of rich administrative data to provide novel insight into coworking couples, a large but understudied group in the labor market. Coworking couples are unique in that they share both a household and an employer, meaning that their labor supply decisions are linked even more closely with the fortunes of their firm than for other households. The extent to which sharing an employer affects spouses' job choice and mobility decisions merits further study.

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A Data Construction Details

A.1 Data Sources

The data for this project come from a series of administrative registers maintained by Statistics Norway. In particular, I use:

- **Individual Data:** I begin with a merged dataset consisting of the **Central Population Register**, **Administrative Tax Records**, and **Norwegian National Educational Database**. This dataset includes all Norwegian residents from 1993-2015. The data include unique individual identifiers, demographics including gender, age, educational attainment and degree type, and location, as well as annual measures of earned income. It also contains household identifiers that allow me to identify married spouses and couples cohabiting with children.

- **Employer-Employee Data:** The **Employer-Employee Register** consists of the universe of work relationships in Norway, from 1995-2014. The data is merged to the **Central Register of Establishments and Enterprises**, a database of all firms public and private in Norway. The resulting dataset consists of one observation per job spell-year, so that workers who work at multiple firms, have multiple contracts at one firm, or switch jobs, have multiple observations. The data include individual identifiers, firm and plant (establishment) identifiers, variables pertaining to the job match such as start and end dates, payrolls, and occupation codes, and firm/plant characteristics like location, organization type, and industry. Because the universal coverage of the data, firm and plant sizes can be constructed by summing up the number of observations per firm-year.

- **Marriages:** I supplement the individual data with another constructed from the **Central Population Register** which gives the year of marriage for all married couples ever observed in the sample. The dataset is left-censored at 1991, so that I do not observe the precise year of marriage for marriages that occur earlier than this, but for all subsequent years I observe the precise marriage year.

- **Firm Performance:** To measure firm performance, I use the **Firm Balance Sheet Register**, which contains detailed balance sheet data for all private sector non-financial firms in Norway from 1995-2015.

- **Firm Ownership:** For some robustness checks, I wish to identify firm owners. I do this using the **Register of Shareholders**, which identifies the shareholders of all limited liability companies and their ownership shares. This dataset covers only 2004-2015.

A.2 Data Construction

Beginning with the employer-employee data, I keep one observation per person-firm-year. This eliminates duplicates observations stemming from workers who are employed at more than one establishment within a firm and workers who experience a change in contracted hours at their employer. I then merge in the individual data, leaving me with a dataset with one observation per person-firm-year. To create a panel at the person-year level, I keep only the highest paying job in each year.

In order to follow married couples both before and after marriage, and identify couples that were coworkers prior to marriage, I then use the marriages data to merge in the identifiers of all spouses an individual ever has in the sample, and the years of marriage for each spouse. I then duplicate an individual's panel records by the number of spouses they have, so that I have a full panel of every *couple* that ever exists. For example, suppose Person 1 is in the sample for 20 years, in which he is single for 5 years, married to Person 2 for 5 years, then married to person 3 for 5 years. I will have 40 total observations of Person 1: 20 years of data linked to Person 2 before, during, and their marriage, and 20 years of data linked to Person 3 before, during, and after their marriage. Under this structure, I identify coworking couples, presently married couples who share an employer, as well as future coworking couples, current coworkers who eventually marry. The final dataset is thus at the couple-year level, including observations of ever-married-couples before, during, and after their marriage.

For my primary analyses, I focus on currently married couples. I also eliminate any couples who ever disagree on being married: that is, if the register does not mutually identify each as married to the other in a given year. This amounts to only 0.17% of all observations. To investigate the interaction of gender and rent sharing, I focus on opposite-sex couples. Finally, I restrict the sample to couple-years where both spouses are working-aged, between 25 and 60, to abstract from human capital formation and retirement.

B Facts about Coworking Couples

B.1 Where Do Coworking Couples Come From?

One important question is whether a given coworking couple is the result of a continued work relationship from before marriage, or a new one formed after after marriage.

First, I focus on couples around the year of marriage, and ask whether it is more likely that the couple is first observed coworking before or after marriage. I define a bandwidth of 5 years around the year of marriage to balance getting a complete picture of coworking behavior and sample size, since for a bandwidth of b, the sample must start in $1995 + b$ to avoid left-censoring. In Table E3 I list the proportion of couples that fall into each of these categories. About 8% of couples first cowork in the 5 years before marriage, while 3.5% first cowork in the 5 years after marriage. This suggests that meeting at work is relatively more common than going on to work together, at least near the year of marriage.

However, it is important to note that, given an average age at marriage of about 30, couples simply have more working years together after marriage than before. Thus, even if coworking first is more common in the 10 years around marriage, it may still be that on the whole most coworking relationships started after marriage simply because there are more couple-years after marriage. The fact that I do not observe the full working life of both spouses makes it difficult to directly account for this possibility. However, as a first pass I try the same exercise as in Table E3 but ignoring censoring and using all observations pre- and post-marriage, enabling me to observe couples up to 19 years before and after marriage. In this case, the couples with many observations pre-marriage will be those that marry late in the sample, while those with many post-marriage marry early in the sample; thus, the latter group will tend to be older. However, if anything this should tend to bias results towards a smaller fraction that were coworkers first, since if the rate of couples meeting at work are declining, the late-sample group would have even higher counterfactual met-at-work rates had they been of marrying age at the beginning of the sample. Table E4 displays the results of this exercise. We see that the same pattern obtains: 10.8% of couples first cowork before marriage while only 4.8% first cowork after marriage.

As an alternative approach, I also plot the fraction of couples that are coworking in each year around marriage; that is, conditioning on distance to marriage. Figure E8 plots this, with Panel (a) being for all couples, while Panel (b) conditions on couples that are both employed in each relative period. In both cases we observe a steep increase in coworking in the 10 years before marriage. In the case of all couples, the rate subsequently decreases steadily. If we condition instead on all couples, we see a sharp spike in the year after marriage, and relative stability thereafter. There is clearly a relevant employment extensive margin here, but the very least it is clear that the total mass of coworking couples does not continue increasing long after marriage: outflows either exceed or are similar to inflows.

B.2 Why Is the Share of Coworking Couples Declining?

As we saw in Figure E3 there has been a consistent, roughly linear decline in coworking rates over time. Over 10% of dual-employed couples worked at the same establishment in 1995, but by 2014 this had declined to 7.5%, or about a 25% drop.

The deep behavioral reasons for this drop merit further study. For example, they may be linked to the rise of online dating displacing other forms of couple formation, as documented in the US in Rosenfeld et al. (2019). However, it is also worthwhile to consider the mechanical reasons by which this decline took place. Consider, for example, changes in the firm-size or gender-ratio distribution. If establishments in Norway are becoming smaller or more gender-segregated, then we would expect the number of coworking couples at each firm to shrink because there are fewer potential spouses. To study this, Figure E9 plots the ratio of the true number of coworking couples over time in each year to the expected number of coworking couples if individuals married at random, holding their employment fixed.[35] From this figure we see that, unsurprisingly, coworking couples are over 400 times as common in reality than if couples matched at random. In addition, even this normalized ratio declines over time, albeit in a less monotonic fashion, meaning that the observed decline is not caused solely by changes in the composition of firms.

Another way to decompose the decline is into the number of couples who meet at work; that is, who are coworkers first and subsequently get married, and a decreased propensity for married couples to work together after marriage. To try and distinguish these two possibilities, I next consider the fraction of couples who met at work. I do not have a way to directly measure whether couples met at work, so instead I proxy this by whether the couple worked together ≤ 5 years before marriage. Figure E10 plots this for new marriages in each year, starting in 2000 to account for left-censoring in observed coworking years. Again, we see a fairly steady decline in this rate over time.

To study changes in the rate of married couples subsequently working together, I next plot the rate of inflows and outflows from coworking-couple status for existing couples over time. Figure E11 plots inflows and outflows of coworking couples as a percent of the total stock of coworking couples in each year. For example, for 1996, the number of new coworking couples in about 17% of the total stock, while the number of couples that stopped coworking is about 14% of the total stock. Overall, both inflow and outflow rates decline modestly over this time period, so that the difference between the two does not change very much; this should not explain the decline in coworking couples over time.

[35] See Appendix D.3 for details on the construction of this random-marriage index.

B.3 Coworking Couples are More Assorted

Given that a striking number of coworking couples work in the same narrow occupation, and that they share an AKM firm effect, it seems plausible that coworking couples will have more similar earnings on average than non-coworking couples. In this section I document that this is indeed the case: coworking couples have a smaller earnings gap than non-coworking couples, and the size of this "wage gap gap" is remarkably stable over time even as overall earnings inequality between husbands and wives declines.

As a first pass, I run regressions of the form

$$\log y_{it}^h - y_{it}^w = \beta \text{Coworking}_{it} + X_{it}'\delta + \varepsilon_{it}$$

Where y_{it}^h is the income of the husband in couple i, y_{it}^w is the income of the wife, and Coworking_{it} is an indicator for being a coworking couple in year t. Table E5 presents the results of this regression for dual-employed couples, and defining coworking at the plant level. We see that coworking couples have a 4.6 log points smaller earnings gap than non-coworking couples, meaning that these couples have significantly more similar earnings than non-coworking dual-employed couples.

To examine the source of this greater equality, Figure E12 plots kernel density estimates of the log earnings gap separately for coworking and non-coworking couples. One striking feature stands out: coworking couples have a very sharp peak at 0; that is, a large number of coworking couples earn exactly the same wage, as in Zinovyeva and Tverdostup (2021). Otherwise, coworking couples seem to be modestly more equal than their non-coworking counterparts, with less mass in the right tail.

The previous regressions showed the average log earnings gap over the sample period. But, does this gap change over time? It might if, for example, the composition of coworking couples was changing over time. In Figure E13 I plot the average log earnings gap separately for coworking and non-coworking couples in each year of the sample. Panel (a) presents the simple averages while Panel (b) presents the coefficients from a regression controlling for the age of the spouses, their education, and location. From the simple averages we see a striking pattern: the earnings gap has come down basically in parallel for coworking and non-coworking couples, with coworking couples always being more equal. The regression results are noisier, but there is no apparent pattern in the coefficients over time. Thus, while men and women (specifically, husbands and wives) have become more equal over time, coworking couples have remained consistently more equal than non-coworking ones, and by a similar amount.

C A Two-Period Model of Rent Sharing

C.1 Setup

Again, we begin with a population of married workers employed at a set of firms. Some of these workers are coworking couples, that is, working at the same firm as their spouse. Workers and firms have linear utility in wages and profits respectively and share a discount factor β. There are now two discrete time periods indexed by $t = 1, 2$. In each period, the timing of the model is identical to the static model in Section 3:

1. Firms realize a productivity shock which translates to a potential surplus π, common across workers at that firm. There are no scale effects or complementarities: the firm treats each worker independently. π is observed by both the firm and the worker.

2. Workers draw an outside wage offer w_o from a distribution $F(\cdot)$.

3. Firms offer workers a wage w, taking into account the surplus of the match π, and the distribution but *not* the specific realization of outside offers.

4. Workers decide whether to stay at their current firm or accept the outside offer. If they switch, they must pay a pecuniary moving cost c, which is higher for coworking couples.

5. If the worker stays, production is realized and split according to the offered w. If not, the firm produces zero and earns no profits.

I assume that there is serial correlation in productivity between the two periods: in particular, the log surplus of a match is AR(1):

$$\log \pi_2 = \rho \log \pi_1 + \varepsilon_2$$

In both periods, the distribution of outside offers $F(\cdot)$ is exogenous. I assume that period-1 outside offers last for both periods: a worker who moves in period 1 will receive w_o in both periods, paying the mobility cost c only in the first period.

C.2 The Second Period

As is often the case with finite-horizon models, it is instructive to begin by studying the terminal period. In this case, the model environment in period 2 is identical to the static model presented in Section 3. The firm's wage offer is determined by Equation (1):

$$w_2 = \pi_2 - \frac{F(w_2 + c)}{f(w_2 + c)}$$

C.2.1 From Individuals to Households

What happens when we consider two-worker households? Note that there are no joint decisions here–since there is no uncertainty at the time of mobility, it is optimal for each spouse to quit if and only if their outside offer net of mobility costs exceeds their inside offer.[36] To make statements about the distribution of household income, it is necessary to parametrize the distribution of surplus. Suppose firms draw iid surplus distributed according to some $G(\cdot)$. Consider an exercise in the spirit of a binned scatterplot: a plot of surplus at a firm against the *average* household income of workers employed there. What we are interested in, WLOG, is $E(w^1 + w^2|\pi^1)$, where the superscripts indicate the spouses. For a non-coworking couple, this is:

$$E(w^1 + w^2|\pi^1) = w(\pi^1) + E(w^2) = w(\pi^1) + \int w(\pi)dG(\pi)$$

As surplus at different firms is assumed independent, so knowing π^1 tells us nothing about π^2. For coworking couples, this is instead

$$E(w^1 + w^2|\pi^1) = 2w(\pi^1)$$

As I assume a common surplus within a firm, and coworking couples share an employer. Thus we see the covariance effect at play: the relationship between firm productivity and household income will be steeper for coworking couples because their individual incomes are more strongly correlated (here, perfectly so).

C.3 The First Period

In the first period, the serial correlation in productivity means that both workers and firms must think about the future. In particular, a higher surplus today implies a higher surplus tomorrow on average, meaning higher wages and profits tomorrow, so that both workers and firms will both have stronger incentives to not break the match.

[36] Note that I am assuming the mobility cost for coworking couples is only experienced upon individual mobility: if spouse 1 moves, spouse 2 does not experience any cost. This is in contrast to a model in which coworking carries with it some amenity, in which case one spouse's decision to move would impose costs on the other by destroying the amenity.

The interaction of this serial correlation with mobility costs is what generates lower income growth for coworking couples. Remember that in period 2, for a given π_2 a worker in a coworking couple will get lower wages, meaning higher profits for the firm. Consider the perspective of a firm in period 1 deciding how much to offer a coworking couple. Since the worker is less mobile, they have a similar incentive to mark down their wages as in the static model. However, they also know that if they are able to retain the worker, they will have *higher* profits next period, because they can pay the worker less and the worker is less likely to leave. This gives the firm a greater incentive to retain the worker this period, which will actually *raise* the offered wage, *ceteris paribus*. These two forces offset each other, implying that the gap between the wages of CWC and non-CWC in period 1 should be smaller. But this in turn implies *lower* income growth between periods 1 and 2 for coworking couples. Put another way:

$$\frac{w_1^{CW}}{w_1^{NC}} > \frac{w_2^{CW}}{w_2^{NC}} \implies \frac{w_2^{NC}}{w_1^{NC}} > \frac{w_2^{CW}}{w_1^{CW}}$$

C.3.1 Solving the Model

While solving the model with simple dynamic programming techniques is straightforward, the continuous distribution $F(\cdot)$ makes a closed-form solution difficult. However, partially solving the model does highlight some of the intuition described above.

Denote by $w_2^*(\pi_2)$ the optimal wage schedule offered in period 2, which will be determined by Equation (1). Consider a worker in period 1 deciding whether to stay or move given an inside offer w_1 and outside offer w_o. The worker stays if

$$w_1 + \beta E_\varepsilon\left[w_2^*(\pi_2)F(w_2^*(\pi_2)+c) + \int_{w_2^*+c}^{\infty}(w_o - c)dF(w_o)\right] \geq (1+\beta)w_o - c$$

Where the expectation on the left hand side is taken with respect to the innovation to surplus, and the expression inside it is the expected wage tomorrow if the worker stays today, accounting for the worker's mobility decision tomorrow. Denote this value function by $W(\pi_1, \varepsilon_2)$. The right hand side is the utility of moving: the worker is guaranteed w_o in both periods, discounts the future at β and pays a mobility cost c today. Then, whether the worker stays depends on their outside offer, and the probability of staying is given by:

$$P\left(w_o \leq \frac{w_1 + \beta E_\varepsilon[W(\pi_1, \varepsilon_2)] + c}{1+\beta}\right) = F\left(\frac{w_1 + \beta E_\varepsilon[W(\pi_1, \varepsilon_2)] + c}{1+\beta}\right)$$

The firm in period 1 chooses a wage w_1 that maximizes the expected discounted present value of profits:

$$\max_{w_1} \left(\pi_1 - w_1 + \beta E_\varepsilon[(\pi_2 - w_2^*(\pi_2))F(w_2^* + c)] \right) F\left(\frac{w_1 + \beta E_\varepsilon[W(\pi_1, \varepsilon_2)] + c}{1+\beta} \right)$$

That is, they take into account the discounted expected profits tomorrow from retaining the worker today. Denote the firm's expected profits tomorrow by $V(\pi_1, \varepsilon_2) \equiv (\pi_2 - w_2^*(\pi_2))F(w_2^* + c)$. It is important to note that this value function does not depend on w_1: it is the benefit from retaining the worker, but doesn't depend on how said worker was retained. Then, this problem yields the first order condition:

$$w_1 = \pi_1 + \beta E_\varepsilon[V(\pi_1, \varepsilon_2)] - (1+\beta) \frac{F\left(\frac{w_1 + \beta E_\varepsilon[W(\pi_1, \varepsilon_2)] + c}{1+\beta} \right)}{f\left(\frac{w_1 + \beta E_\varepsilon[W(\pi_1, \varepsilon_2)] + c}{1+\beta} \right)} \tag{7}$$

Again, the offered wage depends on the firm's value of retaining the worker, which now includes present and future profits. It also depends on the worker's mobility decision. Let us consider two comparative statics: raising π_1 (informative about the relationship between productivity and wages) and raising c (informative about differences in rent sharing for coworking couples).

Obviously, raising π_1 directly increases the offered wage. It also raises π_2 because of the serial correlation, raising expected profits in the second period, also increasing the offered wage. However, it raises the worker's value function in the second period, $E_\varepsilon[W(\pi_1, \varepsilon_2)]$, increasing the Mills ratio, in turn *decreasing* the offered wage. The balance of these forces determines the rent sharing relationship. If the first two terms dominate, there will be positive rent sharing in the first period as in the second.

Raising c directly increases the Mills ratio, lowering the offered wage in period 1, analogous to the static case. However, it also raises $V(\pi_1, \varepsilon_2)$, the firm's expected profits in period 2, which *increases* the offered wage. Furthermore, it reduces the worker's value function $W(\pi_1, \varepsilon_2)$, which lower the Mills ratio and thus also increases the wage. These two offsetting forces are not present in the static model, implying that the coworking "penalty" should be somewhat attenuated in the first period for coworking couples: the difference in offered wages should be smaller. This in turn results in lower income *growth* for coworking couples: they go from being offered similar wages in period 1 to much lower wages in period 2.

C.4 Full Solution and Simulation

The preceding discussion of Equations (1) and (7) provides valuable insight into the key importance of mobility for rent sharing in both levels and growth rates. However, to more clearly illustrate the link, I solve the model fully for a chosen set of parameter values to directly show the implications of the model for individual and household income growth.

The exercise proceeds as follows.[37] First, I fix the distributions of surplus $G(\pi)$ and outside offers $F(w_o)$, and choose values for the parameters of the model. This is done purely for illustrative purposes: the goal is not to match numerical moments in the data, but simply to reproduce the qualitative patterns we observe. I assume that the distribution of outside offers is lognormal with parameters (μ_o, σ_o), and the distribution of log innovations to surplus ε_t is normal with parameters $(\mu_\varepsilon, \sigma_\varepsilon)$, so that the invariant distribution of π_t will be Lognormal$(\mu_\varepsilon/(1-\rho), \sigma_\varepsilon/(1-\rho))$. Table E6 lists the chosen parameters for the exercise. Of particular importance is the higher mobility cost c for coworking couples, at 0.6 versus 0.3 for non-CWC.

Then, for these parameter values, I solve the model numerically using backwards recursion. In the second period, I derive the firm's wage offer schedule $w_2^*(\pi_2)$ by numerically finding the root of Equation (1). Given this wage policy, I then evaluate the firm and worker's expected value functions, $E_\varepsilon[V(\pi_1, \varepsilon_2)]$ and $E_\varepsilon[W(\pi_1, \varepsilon_2)]$, which are the expected profit and expected wage respectively, with the expectation taken with respect to the innovation to surplus ε_2. Given these value functions, I then solve Equation (7) in the same way, deriving the offered wages for coworking and non-coworking couples in period 1. Figure E14 plots these wage offer functions, with the dark lines representing non-coworking couples and the light lines indicating coworking couples. The solid lines are the offers in period 2, while the dashed lines are the offers in period 1. First of all, we see that all the functions are increasing, reflecting the presence of rent sharing: higher surplus leads to higher wages, as expected. Comparing the same-period policy functions, we see a stark difference between periods 1 and 2: while coworking couples receive lower wage offers in both periods, the difference between the solid lines (period 2) is much larger than between the dashed lines (period 1), reflecting the fact that in the first period firms respond to the higher future profits from retaining a coworking couple by marking down their wages less. This in turn illustrates how differences in income growth emerge: coworking couples get a larger relative markdown in period 2 than period 1, so their income growth will be lower on average.

In this particular parametrization of the model, offered wages are lower in period 2 than period 1, meaning that wage growth will be negative on average. This is because all firms in

[37] For more details about the numerical solution, see Appendix D.4.

period 1 expect profits in the future from retaining a worker, which is not the case in period 2, and so are willing to pay more to avoid the worker leaving. This is largely an artifact of the two-period structure of the model, and is not an important feature: the key is the *difference* in growth rates between coworking and non-coworking couples, not the specific levels of these growth rates. It would be easy to rectify this prediction of negative average growth by, for example, introducing a positive drift in π_t, reflecting steady productivity growth over time.

With the wage offer schedules $w_t^*(\pi_t)$ in hand, I then simulate the model. In particular, I start in period 1 by generating pairs of coworking and non-coworking married couples. For each individual, I draw realizations of π_1 from the invariant distribution of the AR(1) process for surplus, where coworking couples receive the same draw while non-coworking couples each receive an independent draw. I compute the offered wages w_1 that correspond to these draws of π_1, draw outside offers w_o from $F(\cdot)$, and simulate the decision to move or stay. For the workers that choose to stay, I then draw innovations ε_2, which determine the period 2 surplus π_2. I again simulate offered wages, outside offers, and mobility. Next, I compute the (log) growth rates of surplus $\Delta\pi = \log(\pi_2) - \log(\pi_1)$, wages $\Delta w = \log(w_2) - \log(w_1)$, and household income $\Delta w^{hh} = \log(w_2^1 + w_2^2) - \log(w_1^1 + w_1^2)$. To maintain comparability with subsequent empirical specifications, I take the sample of *individual* continuers, workers who stay at the initial employer in both periods, and plot binned scatterplots of Δw and Δw^{hh} against $\Delta\pi$ separately for coworking and non-coworking couples.

Panel (a) of Figure E15 presents the results of the simulation for individual income growth. We see first that the model produces positive rent sharing in growth rates: Δw is increasing in $\Delta\pi$ for both coworking and non-coworking couples. However, coworking couples experience persistently lower income growth at every level of firm performance, similar to the empirical estimates of Figure 3.

Panel (b) of Figure E15 instead plots *household* income growth for continuers. We see that now, a clear asymmetry emerges between coworking and non-coworking couples: coworking couples have lower household income growth when the firm does poorly, and roughly similar income growth when the firm does well. This asymmetry results from the interaction of a covariance effect with less generous individual rent sharing. First, coworking couples have a steeper slope in the rent sharing relationship because they work in the same firm, and so are hit twice by the same shock, whereas non-coworking couples receive two independent shocks. Second, as demonstrated in Panel (a) Figure E15 coworking couples have lower individual income growth, which will also translate to lower household income growth. Thus, the red dashed line is steeper than the solid blue line, but also has a lower intercept, producing the observed asymmetric pattern. The model again generates patterns very similar to the data (Figure 8).

D Derivations

D.1 Variance Decomposition

We have $Y_{it}^{hh} = Y_{it}^1 + Y_{it}^2$. Then the growth rate

$$\frac{Y_{it}^{hh}}{Y_{it-1}^{hh}} = \frac{Y_{it}^1 + Y_{it}^2}{Y_{it-1}^1 + Y_{it-1}^2} = \frac{Y_{it}^1}{Y_{it-1}^1}\frac{Y_{it-1}^1}{Y_{it-1}^1 + Y_{it-1}^2} + \frac{Y_{it}^2}{Y_{it-1}^2}\frac{Y_{it-1}^2}{Y_{it-1}^1 + Y_{it-1}^2}$$

$$= \frac{Y_{it}^1}{Y_{it-1}^1}\omega_{it-1} + \frac{Y_{it}^2}{Y_{it-1}^2}(1-\omega_{it-1})$$

Subtract one and substitute the log approximation

$$\Delta y_{it}^{hh} \approx \omega_{it-1}\Delta y_{it}^1 + (1-\omega_{it-1})\Delta y_{it}^2$$

D.2 Welfare Approximation

We are interested in computing the consumption equivalent λ such that:

$$E\sum_{t=0}^{\infty}\beta^t\frac{\left((1+\lambda)(1+g^{cw})e^{-\sigma_{cw}^2/2}e^{z_t^{cw}}\right)^{1-\gamma}}{1-\gamma} = E\sum_{t=0}^{\infty}\beta^t\frac{\left((1+g^{nc})e^{-\sigma_{nc}^2/2}e^{z_t^{nc}}\right)^{1-\gamma}}{1-\gamma}$$

Factor everything that doesn't depend on t out of the summation:

$$(1+\lambda)^{1-\gamma}(1+g^{cw})^{1-\gamma}e^{-(1-\gamma)\sigma_{cw}^2/2}\sum_{t=0}^{\infty}\beta^t E\frac{e^{(1-\gamma)z_t^{cw}}}{1-\gamma} = (1+g^{nc})^{1-\gamma}e^{-(1-\gamma)\sigma_{nc}^2/2}\sum_{t=0}^{\infty}\beta^t E\frac{e^{(1-\gamma)z_t^{nc}}}{1-\gamma}$$

Since z_t^{cw} is normal, we know that

$$(1-\gamma)z_t^{cw} \sim N(0,(1-\gamma)^2\sigma_{cw}^2) \implies Ee^{(1-\gamma)z_t^{cw}} = e^{(1-\gamma)^2\sigma_{cw}^2/2}$$

And likewise for z_t^{nc}. Pulling these out of the sum:

$$(1+\lambda)^{1-\gamma}(1+g^{cw})^{1-\gamma}e^{-(1-\gamma)\sigma_{cw}^2/2}e^{(1-\gamma)^2\sigma_{cw}^2/2}\sum_{t=0}^{\infty}\frac{\beta^t}{1-\gamma} = (1+g^{nc})^{1-\gamma}e^{-(1-\gamma)\sigma_{nc}^2/2}e^{(1-\gamma)^2\sigma_{nc}^2/2}\sum_{t=0}^{\infty}\frac{\beta^t}{1-\gamma}$$

Taking logs, canceling, and using the approximation that $\log(1+x)\approx x$:

$$\lambda + g^{cw} - \gamma\sigma_{cw}^2/2 \approx g^{nc} - \gamma\sigma_{nc}^2/2$$

Which gives us the expression for the consumption-equivalent welfare/willingness-to-pay:

$$\lambda \approx (g^{nc} - g^{cw}) + \frac{1}{2}\gamma(\sigma_{cw}^2 - \sigma_{nc}^2)$$

D.3 Random Coworking Index

Here I describe the construction of the random coworking index from Section B.2. The idea of the index is as follows. Suppose you have a population of N men, indexed by $i = 1, 2, ...N$ and N women indexed by $j = 1, 2, ...N$. Each person works at one of K companies, indexed by $k = 1, 2, ...K$, $K < 2N$. Let M_k be the number of men at company k and W_k the number of women. Suppose men and women match randomly with each other and get married. What would be the expected number of coworking couples in this population, that is, what fraction of couples would work at the same company?

Consider choosing one couple at random. What is the probability that they are a coworking couple? By the multiplication principle there are N^2 ways to form a couple. How many of these are coworking couples? To answer this, first consider–how many coworking couples could be formed in firm k? Again by the multiplication principle, this should be

$$M_k W_k$$

Then, how many coworking couples could be formed in total? The sum over firms of the possibilities per firm:

$$\sum_{k=1}^{K} M_k W_k$$

Since every couple is equally likely, the probability that this random couple are coworkers is simply

$$\frac{\sum_{k=1}^{K} M_k W_k}{N^2}$$

Because this couple was chosen at random, this probability should equal the fraction of coworking couples in the population.

Another way to see this takes advantage of the law of iterated expectations. Suppose WLOG you permute the list of women to form a random matching. Let F be the fraction of couples that are coworking, a random variable between 0 and 1. We want to know $E[F]$, where the expectation is taken over the space of permutations. Suppose instead we choose a single couple at random from this matching. Let I be an indicator that said couple is coworking. Obviously, $E[I|F] = P(I = 1|F) = F$; that is, if we know F% of couples are coworking, and we pick one at random, the probability we pick a coworking couple is F. But then, by the LIE:

$$P(I = 1) = E[I] = E[E[I|F]] = E[F]$$

How was I constructed? By randomly permuting the list of women and then randomly picking a single couple. Then, it's obvious that any possible couple is equally likely, so that $E[I]$ must be equal to the probability that a single man and woman chosen at random from the population are coworkers–which is exactly what we calculated above.

D.4 Two Period Model: Numerical Solution Details

I solve the two period model in R via backward induction. Starting in period 2, I create a 50-point grid of surplus π_2, from 0 to 50, chosen to span the vast majority of the support of the invariant distribution of π. I solve for the offered wage at each point on the grid by numerically finding the root of Equation (1). I then fit a cubic spline over this grid to generate the policy function $w_2^*(\pi_2)$. I then use this policy function to compute the worker and firm's expected value functions

$$E_\varepsilon\Big[W(\pi_1, \varepsilon_2)\Big] = E_\varepsilon\Big[w_2^*(\pi_2)F(w_2^*(\pi_2) + c) + \int_{w_2^*+c}^{\infty}(w_o - c)dF(w_o)\Big]$$

$$E_\varepsilon\Big[V(\pi_1, \varepsilon_2)\Big] = E_\varepsilon\Big[(\pi_2 - w_2^*(\pi_2))F(w_2^* + c)\Big]$$

On the grid via Monte Carlo integration. In particular, I simulate 10,000 draws of ε_2 from a normal distribution, compute W and V at every realization, and take the average. I then fit splines over these value functions. With the value functions in hand, I can then solve the period 1 problem. Starting with the same grid of surplus, I solve for the policy function $w_1^*(\pi_1)$ by finding the root of Equation (7) and fitting a cubic spline over the grid.

Using these policy functions, I simulate the productivity realizations, offers, and mobility decisions of 1,000,000 coworking and non-coworking couples, which I use to produce the binned scatterplots in Figure E15. The period-1 distribution of π_1 is drawn from the invariant distribution of π implied by its autoregressive dynamics, which in this case will be a Lognormal distribution with parameters $(\mu_\varepsilon/(1-\rho), \sigma_\varepsilon/(1-\rho))$.

E Additional Tables and Figures

E.1 Appendix Tables

Table E1: Descriptive Statistics, One Job Sample

	Non-Coworking			Coworking		
	Mean	Median	Variance	Mean	Median	Variance
Δ HH Inc	.0292	.0278	.0177	.025	.0248	.0365
Δ Wife Inc	.0319	.0285	.0878	.0262	.026	.117
Δ Husband Inc	.0243	.024	.0502	.0206	.0209	.0772
Age Wife	43.6	44	70.7	44.2	44	71.2
Age Husband	45.9	46	70.9	46.7	47	70.4
HH Inc (1000 2011 USD)	155	141	5,079	153	138	5,364
Wife Inc (1000 2011 USD)	58.9	55.5	909	61.4	58	1,129
Husband Inc (1000 2011 USD)	95.7	83.2	3,429	91.2	80	2,827
Wife Plant Size	391	53	1,502,727	566	45	3,420,990
Husband Plant Size	380	57	2,152,576	566	45	3,420,990
Kids Under 5	.348	0	.512	.344	0	.525
Kids Under 13	.919	0	1.15	.883	0	1.21
Observations	3,930,863					

Note: Summary statistics for dual-continuer household-years with one job this and last year with both spouses aged 25-60. Income levels deflated using Norwegian CPI and converted to 2011 USD.

Table E2: Linear Rent Sharing Estimate

	(1)	(2)	(3)
	Δy_{it}	Δy_{it}	Δy_{it}
	b/se	b/se	b/se
ΔVA_{jt}	0.025***	0.029***	0.028***
	(0.001)	(0.001)	(0.001)
Controls	No	Yes	Yes
Plant FE	No	No	Yes
R-Sq	0.000	0.050	0.077
Mean Dep. Var	.018	.018	.0181
Observations	5,162,546	5,162,278	5,158,329

Note: Standard errors in parentheses, clustered at the couple level. Controls for age fixed effects, education, location of both spouses, number of kids under 13, and year. ΔVA is the log growth of value-added per worker at the firm level. Sample of continuers in plants with at least 10 employees last year, trimming 1% tails of ΔVA.

Table E3: Cowork or Marry First

	b	pct
no cowork in 5 yrs around marriage	226,725	87.198
first cowork $\leq$ 5 yrs before marriage	20,861	8.023
first cowork in year of marriage	3,451	1.327
first cowork $\leq$ 5 yrs after marriage	8,975	3.452
N	260,012	100.000

Table E4: Cowork or Marry First, No 5 Year Restriction

	b	pct
no cowork observed	419,872	82.867
first cowork before marriage	54,810	10.817
first cowork in year of marriage	7,828	1.545
first cowork after marriage	24,173	4.771
N	506,683	100.000

Table E5: Log Earnings Gap, Coworkers vs. Non

	(1) Log Earn. Diff b/se	(2) Log Earn. Diff b/se
Coworking (plant)	-0.048***	-0.046***
	(0.002)	(0.002)
Controls	No	Yes
R-Sq	0.000	0.067
Mean Dep. Var	.526	.526
Observations	8,723,303	8,719,616

Note: Standard errors in parentheses, clustered at the couple level. Controls for age and age squared, education, location of both couples, and year.

Table E6: Chosen Model Parameters

Parameter	Chosen Value
ρ (AR coefficient, π_t)	0.75
μ_ε (Mean of innovation to π_t)	0.5
σ_ε (SD of innovation to π_t)	0.1
μ_o (Lognormal μ of outside offer)	0
σ_o (Lognormal σ of outside offer)	0.5
c^{NC} (Mobility cost, non-CWC)	0.3
c^{CW} (Mobility cost, CWC)	0.6
β (Discount factor)	0.9

E.2 Appendix Figures

Figure E1: Code of Conduct of Yara International ASA

Relationships between employees

Yara understands that romantic relationships may develop between employees. However, we also recognize that such relationships may affect the work environment for others, and that they may increase the risk of misperceptions, conflicts of interest, and even fraud. If you are in a romantic relationship with a colleague, please pay special attention to the rules on conflicts of interest. If you have concerns about a romantic relationship, we encourage you to seek advice from your line manager.

For romantic relationships within a reporting line or between colleagues within the same team, the highest-ranking person must report the relationship to their line manager, and amicable adjustments should be made.

All reports regarding romantic relationships will be handled with the utmost discretion.

Source: Yara International ASA (2023).

Figure E2: Rent Sharing for Coworking Women, One Job Sample

(a) Men

(b) Women

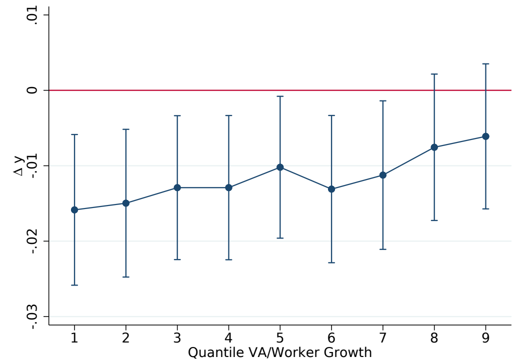
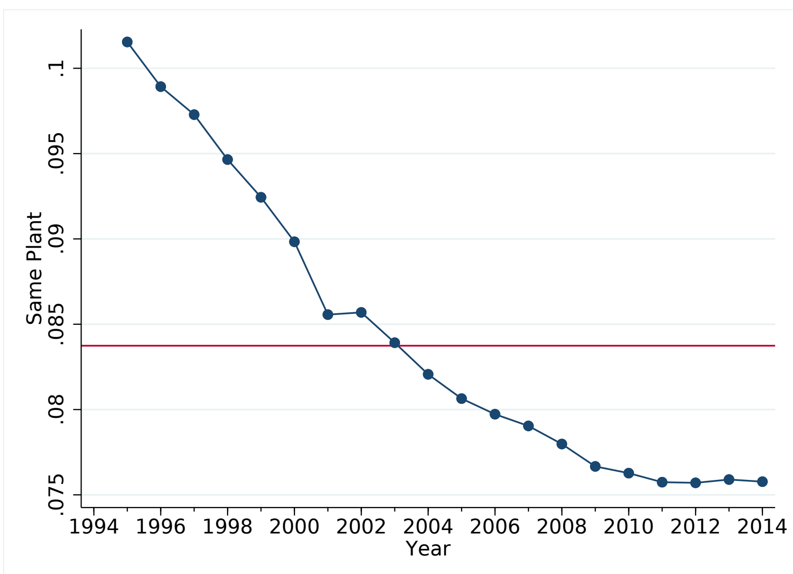


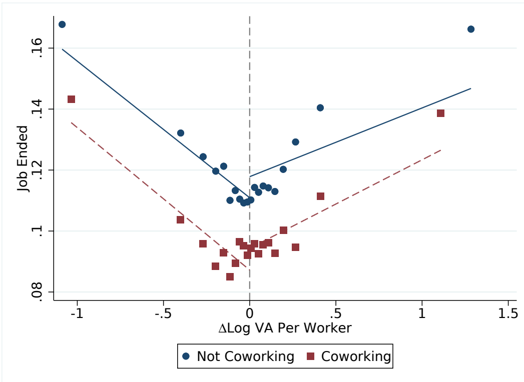
Figure E3: Fraction Coworking Couples by Year



Note: Fraction of dual-employed couples that share a plant by year.

Figure E4: Mobility by Firm Performance, Any Job Ended

(a) Men



(b) Women

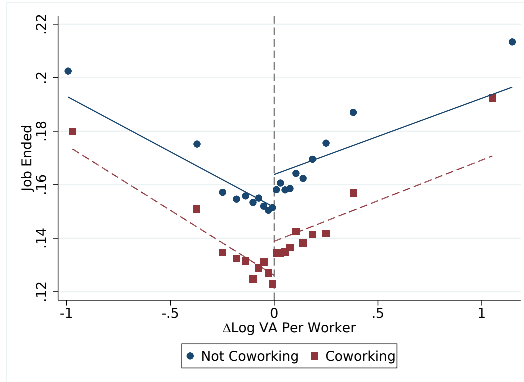
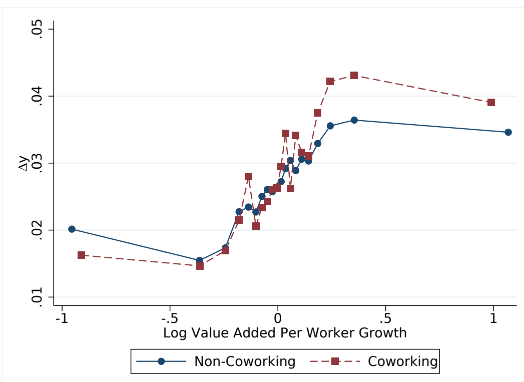


Figure E5: Individual Rent Sharing, Binned Scatterplots

(a) Men



(b) Women

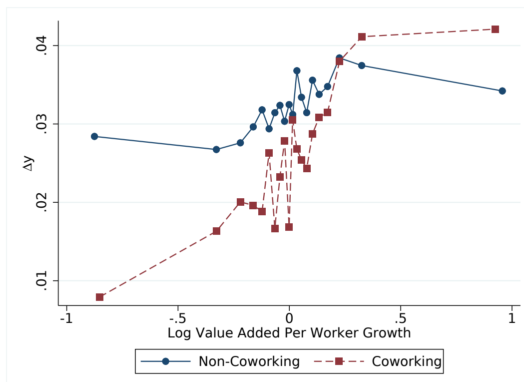
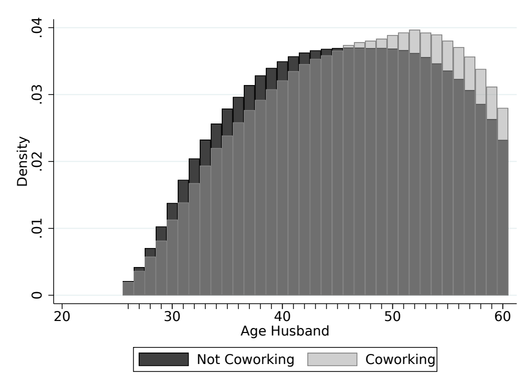


Figure E6: Age Distributions of Coworking and Non-Coworking Couples

(a) Men



(b) Women

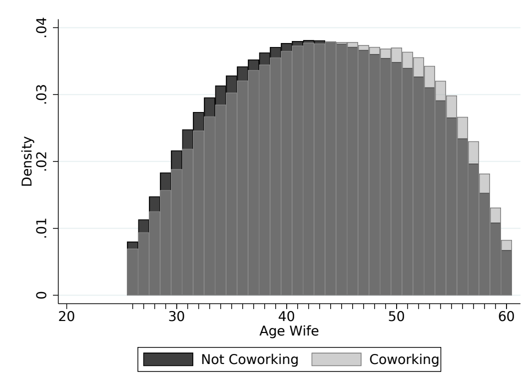
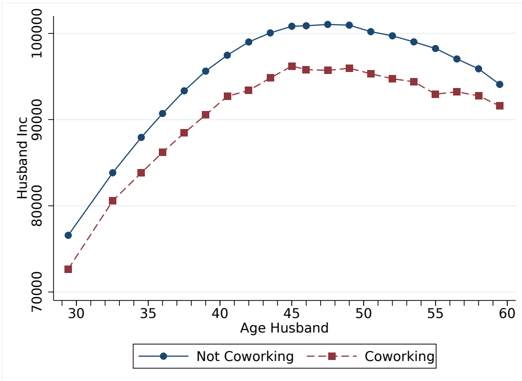


Figure E7: Age Profiles in Income by Gender

(a) Men



(b) Women

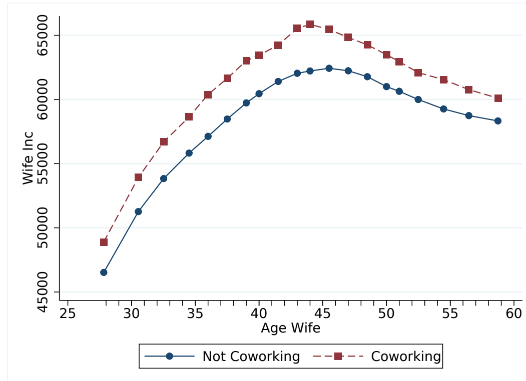
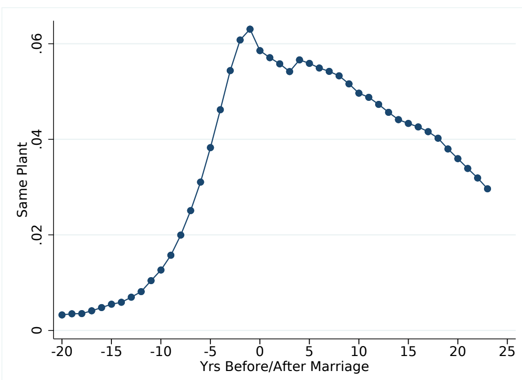


Figure E8: Coworking Rates Around Year of Marriage

(a) All Couples



(b) Dual-Employed

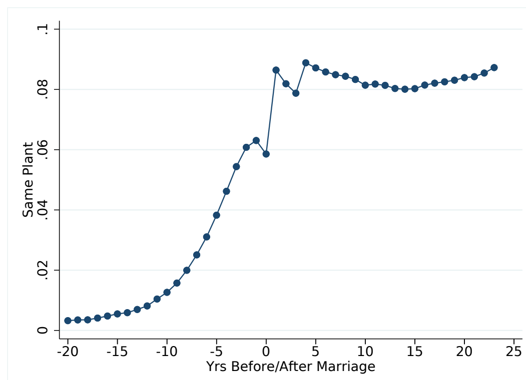


Figure E9: Coworking Relative to Random Matching

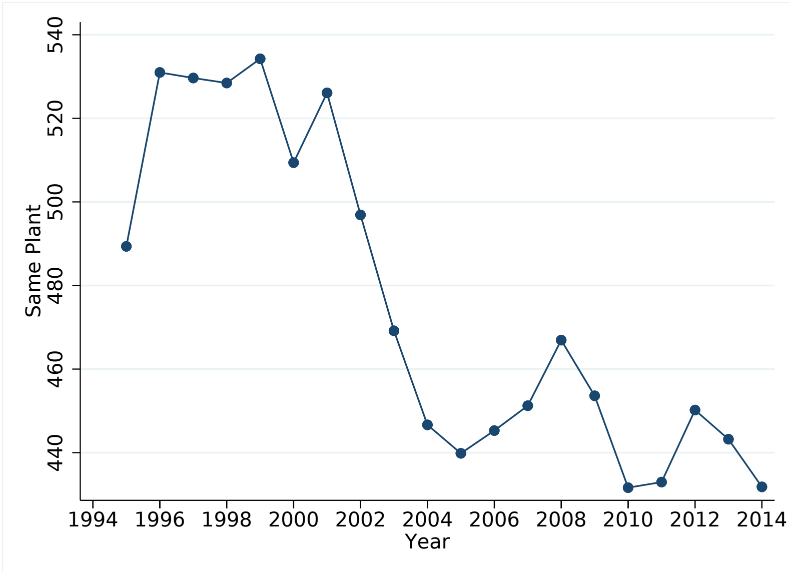


Figure E10: Meeting at Work by Year

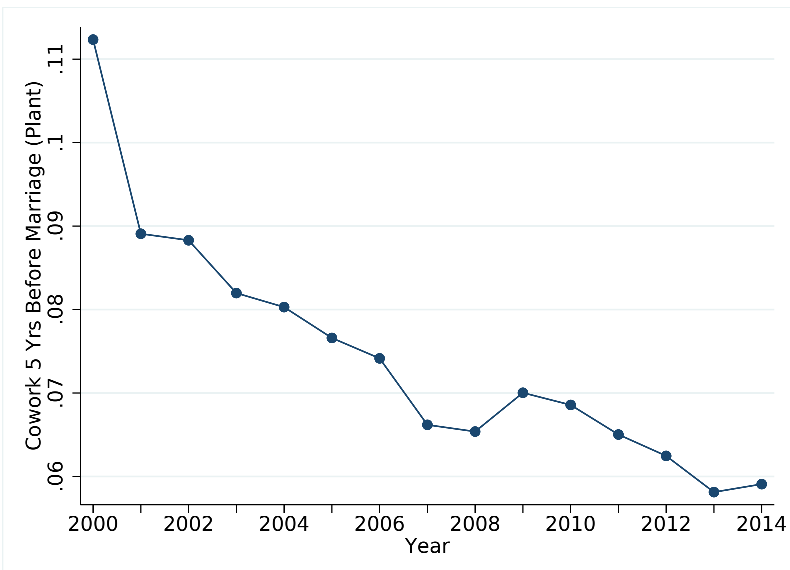


Figure E11: Inflows and Outflows to Coworking by Year

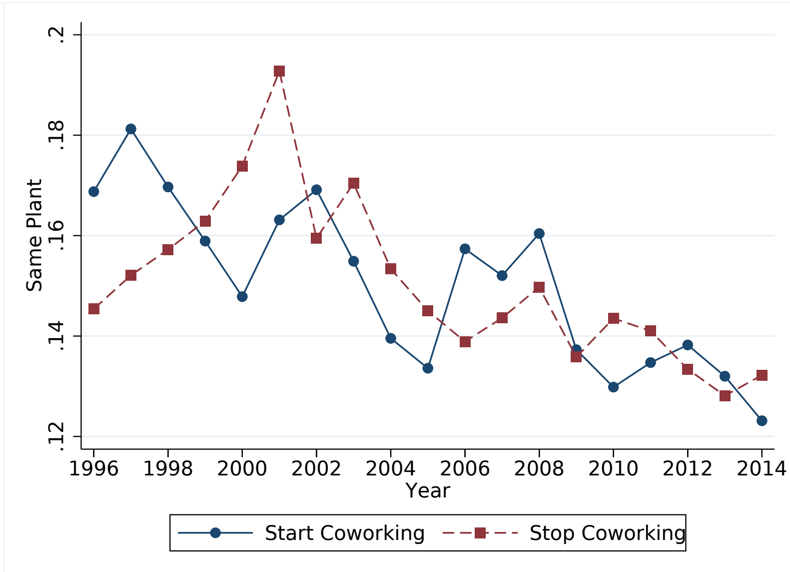


Figure E12: Spousal Earnings Gaps by Coworking, Kernel Density

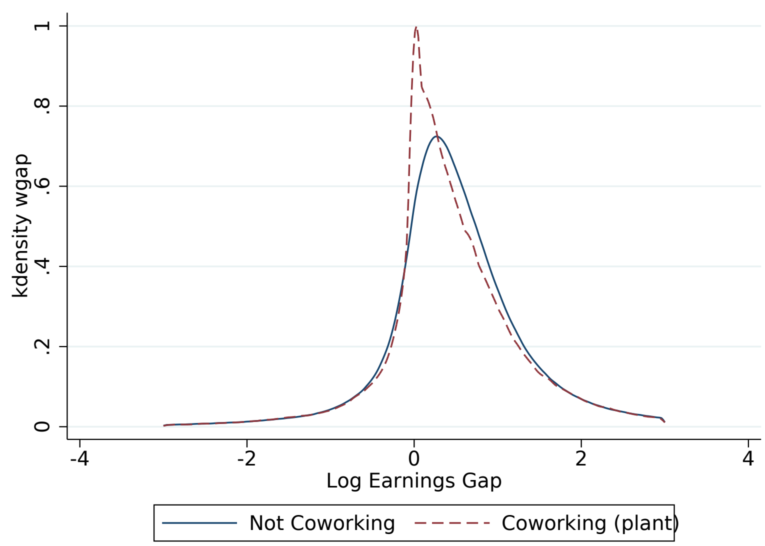


Figure E13: Spousal Earnings Gap by Coworking Over Time

(a) Raw Gap (b) With Controls

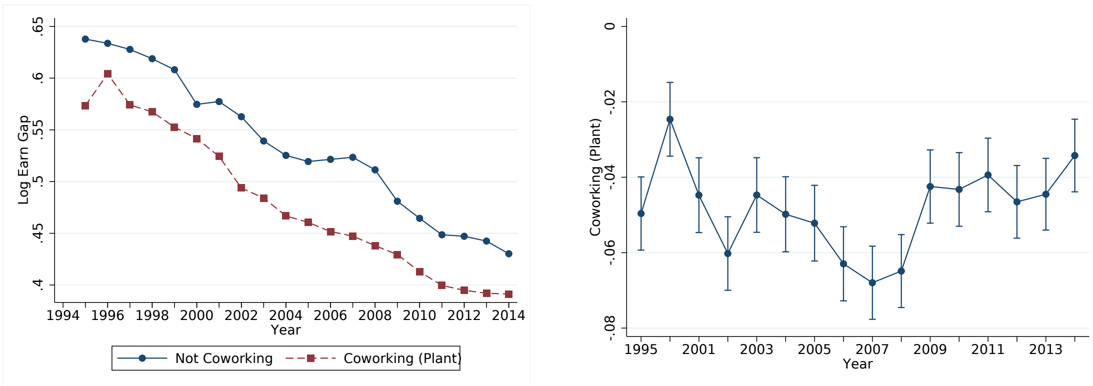


Figure E14: Two Period Model: Offered Wages

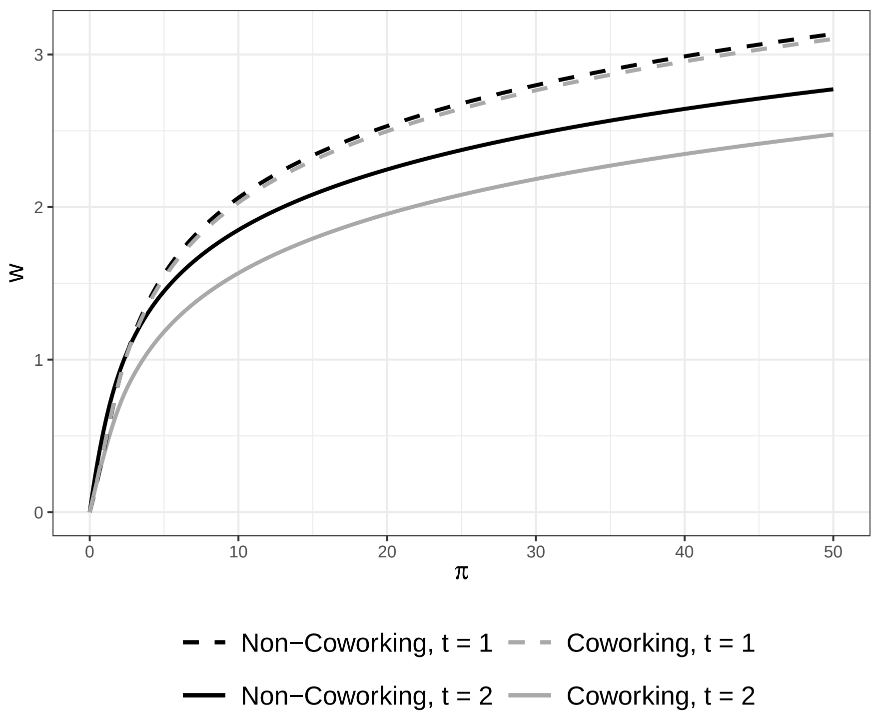
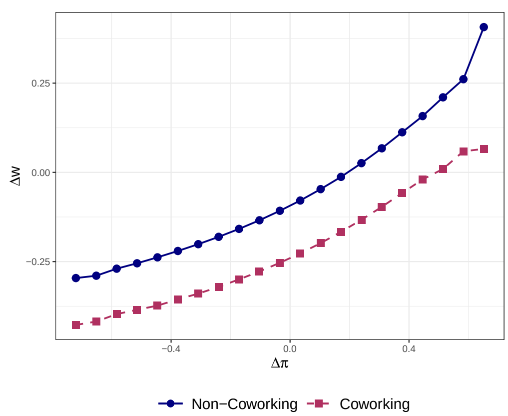


Figure E15: Two Period Model: Rent Sharing

(a) Individual Rent Sharing



(b) Household Rent Sharing