PRODUCTIVITY SPILLOVERS WITHIN FAMILIES AND FIRMS

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Economists have traditionally assumed that people's productivity in the labor market is determined solely by the choices they make over the course of their lifetime and have paid relatively little attention to the possibility that productivity might be influenced by the attributes and decisions of the people they live and work with. This dissertation reports evidence that such productivity spillovers exist, both within households and within firms. The first chapter examines whether a person's work hours are influenced by his/her likelihood of changing marital state. Data from the National Longitudinal Survey of Youth 1979 are used and three different methods for measuring the probability of marriage and divorce are employed. Consistent with theoretical predictions, married women are found to work more when they face a high probability of divorce. This relationship holds both over an individual's life-cycle and across people with different inherent risks of divorce. The second chapter explores whether team-mate performance influences individual performance and salaries in Major League Baseball. Team-mates may inflate a player's output in a single year or they may have a lasting influence on his performance. Evidence of these effects, which are termed spillovers and learning, respectively, are found among both pitchers and non-pitchers. Pitchers are more likely to post low earned run averages if other pitchers on their team achieve low earned run averages in the same season or the previous season. Batters tend to have high batting averages if their team-mates had high batting averages in the previous season. Team performance measures are found to

have some direct influence on salary, however they operate largely indirectly, by augmenting individual performance. Finally, the third chapter examines the effects co-worker ability has on wages in the wider labor market, using matched employer-employee data that have been constructed by the United States Census Bureau. The average levels of education and tenure among a person's co-workers are found to have a positive effect on wages, indicating the presence of human capital spillovers. Co-worker tenure has a bigger impact on new entrants to a firm. In contrast, co-worker education has a larger effect on highly-educated workers.

BIOGRAPHICAL SKETCH

Kerry L. Papps completed his undergraduate education in New Zealand, obtaining a Bachelor of Science degree with first class honours from the University of Canterbury in 1999. In 2000 he was awarded a Master of Commerce and Administration degree with distinction in economics. His thesis was entitled “Wage determination in local labour markets: Theory and evidence for the wage curve in New Zealand” and he was supervised by Associate Professor Jacques Poot. Dr Papps also has a Master of Arts degree from Cornell University, received in 2007. From 2000 to 2001, he worked as a research analyst at the Labour Market Policy Group of the New Zealand Department of Labour in Wellington. Dr Papps traveled to Cornell on a Fulbright Graduate Student Award. Whilst there, he was employed as a research assistant for Professor Robert Hutchens (2001-2003) and Professors Francine Blau and Lawrence Kahn (2003-2007) and worked as a consultant for the Cornell Institute of Social and Economic Research. In addition, he spent the summer of 2003 working as a researcher at Motu Economics and Public Policy Research in Wellington and was employed as a short-term temporary consultant for the World Bank during 2006 and 2007.

For Clare

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Chapter 4 reports the results of research and analysis undertaken by the U.S. Census Bureau staff. This research is a part of the U.S. Census Bureau's Longitudinal Employer-Household Dynamics Program (LEHD), which is partially supported by the National Science Foundation Grants SES-9978093 and SES-0427889 to Cornell University (Cornell Institute for Social and Economic Research), the National Institute on Aging Grant R01 AG018854, and the Alfred P. Sloan Foundation. The views expressed on statistical issues are those of the author and not necessarily those of the U.S. Census Bureau, its program sponsors or data providers. Some of the data used in this paper are confidential data from the LEHD Program. The U.S. Census Bureau supports external researchers' use of these data through the Research Data Centers (see www.ces.census.gov). For other questions regarding the data, please contact

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1. Introduction

Labour economists have long concerned themselves with the productivity of workers in the economy. Productivity, loosely defined as the value of a person's output per unit of time, should determine the amount he/she is paid in any competitive labour market. Although the simplest models of labour supply exclude any possibility that a worker's productivity can change, models of education and training allow a worker to invest in his/her own future productivity and, hence, wage rate. Nonetheless, very few studies have considered the possibility that an individual's productivity can be directly influenced by the attributes and decisions of the people he/she lives or works with.

This dissertation examines the possibility that a person's human capital and wage levels may be affected by the decisions and attributes of the people he/she interacts closely with, specifically the person's spouse and co-workers. Since knowledge can to a certain extent be considered a public good, these effects have been termed productivity, or human capital, spillovers.

Under the most basic textbook models of labour supply, workers have no control over their productivity levels. In the classical static model of labour supply, each worker is paid a fixed wage and chooses only how much time to devote to the labour market. Blundell and MaCurdy (1999) note that this model can be extended to "allow for "wages" to vary as a function of hours of work with relatively straightforward modifications of the subsequent analyses" (p. 1588). However, an inherent weakness of the static model is that it permits no way to distinguish between productivity improvements achieved by on-the-job experience and the effects of a wage schedule that simply rewards long hours, for example overtime pay. Life-cycle models of labour supply typically assume a wage that grows according to an exogenous process, perhaps with a distinction between permanent and transitory income.

Other models explicitly consider the decisions made by individuals (and sometimes firms) about how much human capital to acquire. Models of the return to education usually involve individuals choosing a level of schooling to maximize lifetime utility. Although this relaxes the assumption of the basic labour supply models that productivity is exogenous, schooling is modelled as a one-off decision, with a fixed lifetime stream of income resulting from any choice. Moreover, an individual can only influence his/her own human capital. Becker's (1964) seminal model of on-the-job training similarly involves a decision of whether to undertake firm-specific or general training. Specific training is likely to only take place if worker and firm share the costs, meaning that the human capital of the former is affected by the actions of the latter. However, the firm will only contribute to the training costs if it finds it profitable to do so – there are no externalities and each employee is considered in isolation.

While the mainstream literature has assumed that individuals can determine only their own productivity levels, a number of authors have considered the possibility that productivity spillovers exist. Given the amount of time that adults spend with their spouses and co-workers, it seems reasonable to think that they might be the source of any such spillovers. Data from the 2006 American Time Use Survey indicate that men aged 25 to 54 spend on average 167 minutes per day in the presence of their spouses and 329 minutes at work and work-related activities (and presumably in the presence of work colleagues). Similarly, women aged 25 to 54 spend 162 minutes with their spouses and 217 minutes at work.

The decision to marry is likely to have a major influence on a person's human capital accumulation. Becker (1965) analysed marriage within a utility maximization framework. Under his framework, a person will choose to marry if he/she perceives that the utility from that state will exceed that from remaining single. One benefit of marriage is that it allows couples to specialize in either labor market work or household production. Those married people who specialize in market work are likely to acquire more human capital than single people and thus should experience faster-growing wages. Since individuals aim to maximize *lifetime* utility, not only should their current marital state influence their degree of labor market specialization, but also their expectations of future changes in marital state. For example, once married, the likelihood of divorce may influence a person's decision of how much time to spend in the labor market.

In Chapter 2, I examine how the work hours of married men and women are affected by their likelihood of divorce, as well as how single people are influenced by the probability of marriage. I present the first dynamic model of labour supply in the presence of marital instability, wherein individuals face a certain probability of changing from married to single or *vice versa*. This implies that the probability of marriage increases work hours by unmarried people if their expected marginal utility with respect to hours is higher in the married state than in the unmarried state. Similarly, the divorce probability will have positive effect on hours if a person has a marginal utility that is higher in the unmarried state but a spouse with marginal utility that is higher in the married state. Under the assumption that men earn more than women, I show that this means that single women work less when marriage is likely and married women work more when divorce is likely, while the conclusions for men are the reverse. A major issue in the empirical analysis is how to measure the marital transition probabilities. Drawing on data from the National Longitudinal Survey of Youth, I take three different approaches to measuring the probabilities of marriage and divorce and find broad support for the predictions of the theory.

People's work colleagues may also influence their human capital, but for different reasons to intra-household spillovers. While spouses may be viewed as complements in production, to the extent that they have different skills that are valuable to the household, employees within a firm may be considered substitutes, insofar as they share many of the same skills. Workers might learn from highly productive co-workers or managers or there may be pure spillovers where a person benefits from working alongside talented colleagues without acquiring any permanent increase in ability.

One of the earliest papers to consider the effect of human capital spillovers within firms was by Mayer (1960). He provided a very simple example, whereby a worker of ability P_2 has the choice of working alone and receiving a wage equal to P_2 or supervising s less able workers with average ability P_1. In the latter case, he is able to "pass on" his ability, meaning that his total profit is $s(P_2 - P_1)$. He will choose this option so long as $s(P_2 - P_1) \geq P_2$, with equality for the marginal entrepreneur. It is also possible to have a third hierarchy level, whereby the most able individuals (who have skill P_3) hire some of the first-stage entrepreneurs previously described. The profit earned by these second-stage entrepreneurs is $s^2(P_3 - P_2)$ and the marginal entrepreneur must satisfy $s^2(P_3 - P_2) = s(P_3 - P_1)$.

In Chapter 3, I investigate whether productivity spillovers exist in a very special industry – major league baseball. A key advantage of analysing sports data is that they include many detailed measures of individual and team productivity, or performance. I exploit a rich dataset containing annual information on all major league players and look for evidence of transitory, or "pure", productivity spillovers and long-lasting productivity spillovers, or "learning". Evidence of the former is found for pitchers only, while evidence of the latter is found for both pitchers and non-pitchers. Since team-mate performance directly influences individual performance, it is easy to understate the effect of former on earnings over a player's career. For that reason, I estimate the short- and long-run salary effects of team-mate performance. Pitchers are paid better if they play for teams with weak pitching and hitting, whereas non-pitchers are paid better if they play alongside hitters with high averages and who walk often, with much stronger effects over the course of a player's entire career.

Finally, in Chapter 4, I attempt to generalise the analysis of intra-workplace spillovers to the entire labour market by using matched employer-employee data that have been assembled by the Longitudinal Employer-Household Dynamics programme at the United States Census Bureau. These data are based on each state's unemployment insurance records and allow the researcher to follow a worker from job to job over his/her entire career and also to identify all of the person's co-workers in any job at any point in time. However, as mentioned above, unlike in professional sports, few direct measures of productivity are available in the wider labour market. Since it is based on administrative records, the matched employer-employee data contain even fewer. One desirable productivity measure is job tenure. This can be calculated from the data, however there is a missing data problem arising from the fact that retrospective job start information is not available for those jobs that commenced before a state began contributing data to the programme. To circumvent this problem, I impute missing values for job start date using multiple imputations techniques and drawing on additional data from the Survey of Income and Program Participation. I then use the completed tenure variable in a set of earnings equations, along with years of schooling. The average tenure and education level at an establishment are found to have a positive effect on the earnings of both men and women. Average tenure has a bigger impact on new entrants to a firm, while average education has a larger effect on the most highly-educated women in a firm but roughly the same effect on men.

Taken together, these studies indicate a significant, if modest, role of spillovers within families or firms. Less specialisation takes place within “unstable” marriages, while people are more productive when they are surrounded by highly-able colleagues.

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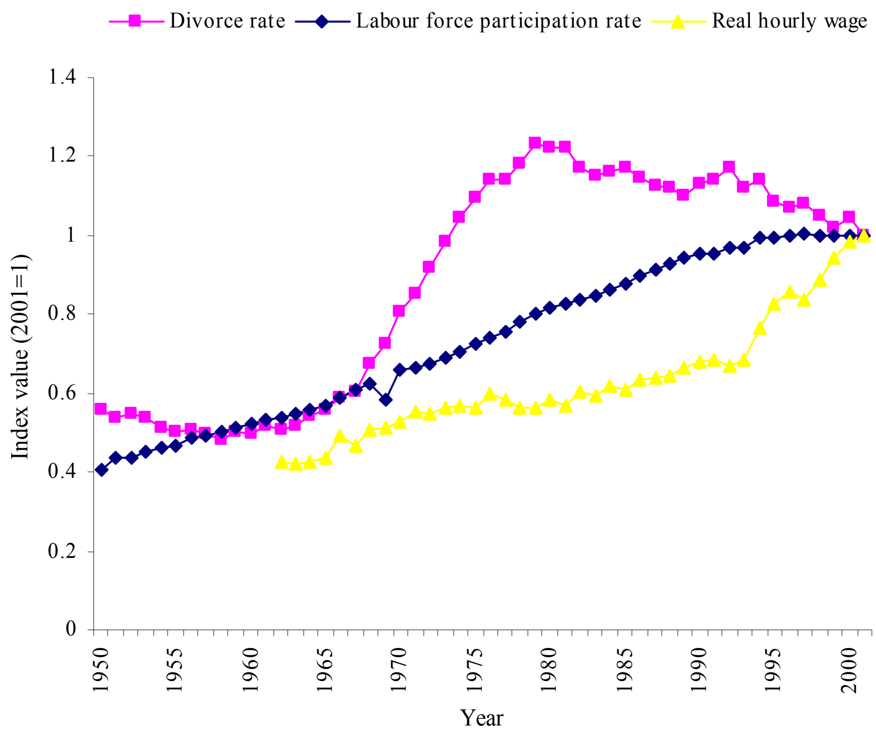
2. The effects of divorce risk on the labor supply of married couples

"A divorcée is a woman who got married so she didn't have to work,
but now works so she doesn't have to get married."
ANNA MAGNANI

It is a commonly-held assumption that married men earn more than unmarried men because they are able to specialize in labor market work and, hence, acquire more human capital, while their wives perform the bulk of unpaid tasks within the household. In this case, the event of divorce should have important economic consequences for both husband and wife. Divorced men are likely to experience declining wages relative to men who remain married, as their accumulated human capital gradually depreciates. Women are likely to be forced to enter the labor market or increase their hours of work after divorce and be paid less than single women, who have more human capital. However, if women make labor supply decisions optimally, taking into account the probability of their marriage dissolving, then they may choose to devote more time to market work while still married, in order to boost their future earnings capacity in the event of divorce. Presumably, the higher the probability of divorce is, the more hours a married woman will want to work. This phenomenon should be observed both across groups with different divorce rates and over time, as couples assess the quality of their match and decide whether to continue their marriage.

Figure 2.1 displays the evolution of the labor force participation rate among married women in the United States over the past half-century, as well as the number of divorces per 1000 married women and the real hourly wage for employed married women. The labor force participation rate reached a plateau in the 1990s after four



Sources: Divorce rate (divorces per married women aged 15 and over): Clarke (1995) and author's calculations, based on data from National Center for Health Statistics; labour force participation rate: United States Census Bureau (2003), based on Current Population Survey data; wage rate: author's calculations based on March Current Population Survey data.

Figure 2.1
Trends in labor force participation, divorce and wages among married women

decades of steady growth. Meanwhile, the divorce rate rose sharply in the 1960s and 1970s, before declining somewhat. Wages grew in most periods, but most steeply in the 1990s.

Previous research has largely attributed the post-war increase in female participation in the United States labor market to growth in the real wage offered to women. However, estimates suggest that this can only explain around half of the total increase in female participation rates. Furthermore, Shapiro and Shaw (1983) noted that during the 1970s, labor force participation by married women continued to grow, despite a stagnant real wage, as seen in Figure 2.1. More recently, Blau and Kahn

(2007) presented evidence that married women's labor supply function shifted significantly to the right in the 1980s, with little movement in the 1990s, and that the difference in this shift accounted for the more dramatic growth in female labor supply during the former decade. Given that divorce rates were increasing prior to the 1980s and fell leading into the 1990s, it is plausible that these puzzles may at least in part be explained by a reaction of women to changes in marital instability.

Apart from a strand of literature investigating the effect of divorce law reform, few previous studies have examined the effect that the threat of divorce has on the labor supply decisions of married couples and none of these has presented any theory that might explain this behavior. As Lundberg and Pollak (1996) noted, if "the analysis of marriage and divorce is awkward, the analysis of marital decisions in the shadow of divorce is even more so" (p. 143). Furthermore, previous papers have used only cross-sectional data or a few years of panel data and have thus been unable to examine whether individuals respond to changes in divorce probability from period to period or whether the relationship strictly occurs *across* people.

This paper represents the first attempt to model the effect both marriage and divorce probabilities have on labor supply and wages within a utility maximization framework. I develop a theoretical model that is based on a setting in which men and women each maximize their own lifetime utility and married couples interact in a non-cooperative manner. Wages are determined by the number of hours a person has worked in the past. The probability of marriage is found to increase work hours for those unmarried people who expect to marry someone with a lower wage rate. This is more likely to be the case for men than women. Conversely, among married couples, an increase in the likelihood of divorce has a positive effect on labor supply for those who earn less per hour than their spouses: something that is likely for women but not men.

This model is then tested using data from the National Longitudinal Survey of Youth (NLSY) 1979 for the period 1979-2004. Cox proportional hazard models are used to generate estimated probabilities of marriage among single people and divorce among married people each period, unlike previous studies, which use probit specifications and do not consider never-married people. The estimated marriage and divorce probabilities are then used as explanatory variables in labor supply regressions. For those in their first marriage, a 0.01 increase in the annual probability of divorce results in a wife working around 60 extra hours a year, consistent with theoretical predictions. Higher marriage probabilities are associated with increases in the hours worked by single men, but also among single women. These relationships persist both across individuals and over a person's life-cycle, indicating that inter-temporal maximization with respect to divorce risk occurs. For the first time, I also uncover evidence in support of the theoretical predictions using individuals' evaluations of how satisfied they are with their marriages as a proxy for divorce risk. These data provide a clearly exogenous measure of divorce likelihood and suggest that women who are unhappy with their marriages work significantly more than other married women.

The next section provides an overview of past work examining the relationship between wages, labor supply and divorce, before I present my theoretical model. After describing the NLSY dataset, I then discuss my empirical strategy and results.

1. Literature review

Numerous previous studies have established that married men have higher earnings than never-married men. Although it continues to be the subject of debate, one persuasive explanation for this is that married men are more productive because they are able to devote more time to labor market activities and, hence, accumulate more human capital, while their wives specialize in household production.[1] If intra-marriage specialization is important, one should also expect adjustments to wages and labor supply for both men and women after marriages dissolve. In general, studies indicate that divorce tends to result in higher labor force participation rates for women, although this relationship seems to have weakened over recent decades.[2] Furthermore, men's wages appear to fall after divorce.[3]

Haurin (1989) was notable in that he presented a model of utility maximization that can explain the relationship between labor supply and divorce. In this model, there are two periods and women choose work hours to maximize utility in the face of uncertainty over the employment prospects of their husbands in the second period. Divorce can be viewed as one possible (extreme) shock to a husband's labor supply, since it is treated as being equivalent to a husband not working at all. Haurin shows that leisure demanded by a married woman in the second period is negatively related to the deviation of her husband's work hours from the expected amount.[4] He tests this relationship using data from the National Longitudinal Survey of Mature Women.

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[1] Korenman and Neumark (1991), Daniel (1992), Blackburn and Korenman (1994), Gray (1997), Chun and Lee (2001) and Cohen (2002) all found support for the so-called "productivity hypothesis", whereas Jacobsen and Rayack (1996), Loh (1996) and Hersch and Stratton (2000) concluded that productivity differences cannot explain the marriage premium. In addition, Nakosteen and Zimmer (1987), Cornwell and Rupert (1997) and Millimet *et al*. (2004) reported evidence in favor of the rival "selection hypothesis", whereby men who are more productive in the labor market also tend to be more likely to marry.

[2] Johnson and Skinner (1988) found that women increase their labor supply after divorce, although this is mostly due to an increase in labor force participation than in work hours. Seitz (1999) noted that, among whites, remarried women have higher labor force participation rates than women in their first marriage, but that there are no significant differences between the participation rates of black women who are single, divorced, married or remarried. In contrast, Bedard and Deschênes (2005) concluded that divorce has no effect on female labor force participation, although it does increase hours and weeks of work.

[3] Gray (1997) reported a negative relationship between wages and years since divorce or separation, although the causes of this have changed over time. Ahituv and Lerman (2005) found that for men, divorce results in a fall in wages and hours worked relative to a continuing marriage.

[4] It should be noted that, unlike the model presented later, Haurin explains labor supply responses to *actual* divorce, not the risk of divorce in the future.

Consistent with predictions, divorce is found to induce the largest labor supply response among women, relative to widowhood or a husband's unexpected unemployment or health deterioration.

To the best of the author's knowledge, only six papers have explicitly examined the effect anticipated divorce *risk* has on labor supply. Greene and Quester (1982) used United States Census Bureau data to create predicted divorce probabilities for women based on their demographic characteristics, using a model of marital dissolution developed earlier by Orcutt *et al*. (1976). They found that among married women, labor supply increases with divorce risk.

Johnson and Skinner (1986) estimated a simultaneous model of future divorce probability and labor supply among married woman using PSID data for 1972. Their approach was to obtain predicted probabilities of future divorce from probit equations and use these in labor force participation regressions in place of actual divorce. They found that women increase their labor force participation in the three years prior to separation, noting that the increases in the divorce rate may explain one-third of the increase in female labor supply over the past half-century. Gray (1995) took a very similar approach with NLSY 1979 data for 1988 and also found that women who experience divorce within three years are more likely to work than other married women, *ceteris paribus*. Conversely, a married woman's labor force participation decision has no influence on her probability of divorcing within the following three years.

Like Johnson and Skinner, Montalto and Gerner (1998) examined PSID data, however they considered both men and women and used fifteen years of observations, rather than a single baseline year. A drawback of this was that only a limited number of variables were available.[5] Montalto and Gerner estimated first-stage probit equations for both divorce among married people and remarriage among divorcés and divorcées. Results from their second-stage labor supply equations suggest that expectation of divorce is positively associated with labor force participation and hours among married women, while expectation of remarriage is negatively related to labor force participation by divorced women. Among men, probability of divorce reduces labor force participation and probability of remarriage increases participation.

Austen (2004) analyzed Australian data and used a Cox proportional hazard model to estimate divorce hazard rates for women in 1991. She found that a 10 percentage point rise in the risk of divorce would increase the probability of a married woman working full-time by 13.8 percentage points.

Unlike the other five papers, Sen (2000) constructs a longitudinal dataset and compares two cohorts: the NLSYW for 1968-1983 and the NLSY 1979 for 1979-1993. Her measure of divorce risk was a dummy variable indicating whether divorce or separation occurred in the next three years. To control for the potential endogeneity of future divorce, Sen tried both using the age at time of marriage as an instrument and substituting the predicted probability of divorce from an unspecified probit equation in place of actual divorce. Her results suggest that the risk of divorce significantly increases labor supply, but by less in the more recent cohort.[6]

One further paper uses time series techniques to analyze aggregate time series data for the divorce rate and the labor force participation rate among married women.

[5] Most significantly, Montalto and Gerner have no information on respondents' marital histories. Other than the differences in functional form, their divorce probability variable is identified solely by spousal characteristics, which all other authors enter as regressors in the labor supply equation. The authors also include employment status in the divorce and remarriage probit equations, counter to the argument that this variable is endogenously determined.

[6] Although both Montalto and Gerner and Sen used panel datasets, neither considered panel estimation techniques for the divorce or labor supply equations.

Bremmer and Kesselring (2004) found that an increase in the divorce rate results in a long-run increase in the participation rate.

In addition to these studies, a strand of literature has developed which utilizes exogenous changes in divorce laws to examine the effect the costs associated with divorce have on the labor supply decisions of married women, while circumventing the problems associated with the endogeneity of these variables. These papers rely on a natural experiment, whereby states implemented "no-fault" divorce legislation at different times. No-fault laws are assumed to reduce the costs associated with divorce. Their effect on the incidence of divorce is less clear-cut and there is no consensus in the literature on whether there is a significant relationship.[7]

Among the papers examining the labor market effects of divorce law changes, Peters (1986) and Parkman (1992) both used Current Population Survey (CPS) data and found that no-fault divorce legislation increases labor participation rates among married women. Parkman attributed this to the fact that women who do not participate in the labor market during marriage receive less compensation for their loss of human capital under no-fault laws. This is because these laws reduce the bargaining power of women and, instead, place more importance on property division laws, which recognize only physical and financial assets and ignore human capital. In response, married women in no-fault states are more likely to work in order to insulate themselves from the potential costs of divorce.

Using data from the Census, CPS and PSID, Gray (1998) extended the argument that marital property laws have an important effect on the work decisions of married women by looking at the interaction between the type of property law and no-fault

[7] Among others, Allen (1992) and Friedberg (1998) reported that no-fault laws increased the likelihood of divorce, while Peters (1986) found no effect. Recent evidence by Wolfers (2006) suggests that while divorce law reform leads to higher divorce rates during the first decade after the change in law, it has no long-term effect on the divorce rate.

legislation. He found that a move to no-fault divorce is associated with a decrease in labor supply among married women in states with property laws that tend to favor the husband but an increase in labor supply in states with property laws that tend to redistribute assets to the wife, noting that this is consistent with a bargaining model of marriage where non-market time is divided between leisure and household production. In contrast, Chiappori *et al*. (2002) reported that married women tend to work fewer hours in states where divorce law is favorable to women and *vice versa*.

2. Theoretical model

In this section, I present a model of labor supply in which individuals choose their hours of work in each period to maximize lifetime utility. Unmarried people take their wage rate and the probability of marriage as given, while married people take their own wage rate, their spouses' wage rate and the probability of divorce as given. Wages are determined by past hours of work. In contrast to other models of the division of labor within marriages, our approach assumes a non-cooperative relationship between spouses, so that the hours worked by each constitute a subgame-perfect Nash equilibrium.[8]

a. Structure of model

Consider the population of married people. In each period, their utility is strictly concave in consumption, *C*, and weakly concave in home production, *H*:[9]

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[8] Other approaches are cooperative decision making, *e.g*. Daniel (1992), or cooperative bargaining, *e.g*. Lundberg and Pollak (1993). Lundberg and Pollak (1996) provide a comparison of the three frameworks. One previous paper that considered labor supply and marital status over the life-cycle is van der Klaauw (1996), who analyzed the marriage and labor force participation decisions of women.

[9] Allowing for a utility function that is strictly concave in *H* complicates the model significantly. It should be noted that similar models, such as that of Iyigun (2005), feature utility functions that are weakly concave in both *C and H*.

$$u(C,H) = \ln C + \delta H \ . \qquad (2.1)$$

Consumption is derived from one's own earnings, which are the product of wages, w, and hours of work, n, the earnings of one's spouse and the couple's non-labor income, $2R$. A fraction of one's total income, $1-\lambda$, is conferred to one's spouse. This assumption is in contrast to the income pooling assumption made under the common preference approach to family behavior.[10] Non-wage income is shared equally between the couple, so that each receives R.

Home production is equal to the total hours spent at home by the married couple. It is a public good, insofar as the same amount is available for consumption by both husband and wife (see, for example, Iyigun (2005)). I do not model leisure and normalize the total hours to be devoted by each person to work and home production to be 1. Hence, the maximum possible amount of home production for the couple in any period is 2.

Throughout, barred variables and parameters will refer to husbands and unbarred variables will refer to wives. The wife's utility in any period, t, is then given by:

$$u(w_t, n_t, \overline{w}_t, \overline{n}_t, R_t) = \ln(\lambda w_t n_t + (1-\overline{\lambda})\overline{w}_t \overline{n}_t + R_t) + \delta(2 - n_t - \overline{n}_t)\,, \qquad (2.2)$$

and the husband's by:

$$u(w_t, n_t, \overline{w}_t, \overline{n}_t, R_t) = \ln((1-\lambda) w_t n_t + \overline{\lambda}\overline{w}_t \overline{n}_t + \overline{R}_t) + \delta(2 - n_t - \overline{n}_t)\,, \qquad (2.3)$$

where $\overline{R}_t = R_t$.

Competitive asset markets are assumed, meaning that all non-labor income grows at the rate r, which can be interpreted as the interest rate:

$$R_{t+1} = (1+r)R_t\,; \qquad (2.4)$$

$$\overline{R}_{t+1} = (1+r)\overline{R}_t\,. \qquad (2.5)$$

In any period, log wages are assumed to be equal to one's accumulated stock of

[10] If $\lambda = \overline{\lambda} = ½$ then we would have income pooling, however, in this case, the model reduces to situation where only the spouse with the higher wage works at all.

human capital.[11] Each period, the stock of human capital depreciates at rate ρ but is augmented by the amount θn_t. Hence:

$$\ln w_{t+1} = (1-\rho)\ln w_t + \theta n_t ; \quad (2.6)$$

$$\ln \overline{w}_{t+1} = (1-\overline{\rho})\ln \overline{w}_t + \overline{\theta}\overline{n}_t . \quad (2.7)$$

Between any two adjacent periods t and $t+1$ there is an exogenous possibility that the pair will separate. This happens with probability γ_t. An unmarried woman's single-period utility is:

$$u(w_t, n_t, R_t) = \ln(w_t n_t + R_t) + \delta(1-n_t), \quad (2.8)$$

where $R_{t+1} = (1+r)R_t$ if the individual separated between periods t and t+1, *i.e.* divorcing couples split non-wage income equally. An unmarried man's utility is analogous. Marriage (or remarriage) occurs between periods with probability η_t. Marrying couples pool their non-labor income, so that $R_{t+1} = \overline{R}_{t+1} =$ $(1+r)(R_t + \overline{R}_t)/2$. The marital transition probabilities are revealed at the beginning of each period and are independent, *i.e.* $E_t\gamma_{t+j} = E(\gamma_{t+j})$ and $E_t\eta_{t+j} = E(\eta_{t+j})$, $\forall j > 0$.

Utility is assumed to be time separable and all individuals are assumed to live for T periods and have the same discount factor, β, so that lifetime expected utility is given by:

$$U(C_t, H_t) = \sum_{j=0}^{T} \beta^j E_t u(C_{t+j}, H_{t+j}) . \quad (2.9)$$

In each period, a person chooses his/her work hours in order to maximize lifetime utility, taking all other variables as given. The choice of hours determines the following period's wage. In other words, n is the control variable and w is a state variable.

My approach will be to solve the problem recursively, determining an exact solution for the final period first, before approximating a solution in all earlier periods.

[11] Equations 6 and 7 imply that wages are an increasing function of human capital.

b. Solution in the final period

An unmarried woman's problem in period *T* can be written:

$$V_T^U(w_T, R_T) \equiv \max_{n_T} \{\ln(w_T n_T + R_T) + \delta(1 - n_T)\}. \quad (2.10)$$

The solution to Equation 2.10 is:

$$n_T^{U*} = \frac{1}{\delta} - \frac{R_T}{w_T}. \quad (2.11)$$

Equation 2.11 implies an indirect utility function of the following form:

$$V_T^U(w_T, R_T) = \ln\frac{w_T}{\delta} + \delta(1 - \frac{1}{\delta} + \frac{R_T}{w_T}). \quad (2.12)$$

Similarly, a married woman's problem in period *T* is:

$$V_T^M(w_t, \overline{w}_t, \overline{n}_t, R_t) \equiv \max_{n_T} \{\ln(\lambda w_T n_T + (1 - \overline{\lambda})\overline{w}_T \overline{n}_T + R_T) + \delta(2 - n_T - \overline{n}_T)\}. \quad (2.13)$$

The solution is:

$$n_T = \frac{1}{\delta} - \frac{(1 - \overline{\lambda})\overline{w}_T \overline{n}_T + R_T}{\lambda w_T}. \quad (2.14)$$

Equation 2.14 represents what I will term the married woman's "labor supply response function". This is not a labor supply function, because $\overline{n}_t$ is not exogenous but, rather, is determined by the utility maximization of the woman's husband. A married man's labor supply response function is analogous to Equation 2.14:

$$\overline{n}_T = \frac{1}{\delta} - \frac{(1 - \lambda) w_T n_T + \overline{R}_T}{\overline{\lambda}\overline{w}_T}. \quad (2.15)$$

Husband and wife determine their optimal hours of work simultaneously according to Equations 2.15 and 2.14, respectively. For a Nash equilibrium in the period *T* subgame, both spouses must choose a level of *n* that is a best response to the other's value. Since each labor supply response function is a linear function of the spouse's work hours, there is a unique Nash equilibrium, akin to the case of a Cournot duopoly. Making the assumption that $\lambda > ½$ and $\overline{\lambda} > ½$ (*i.e.* neither spouse gives more than half

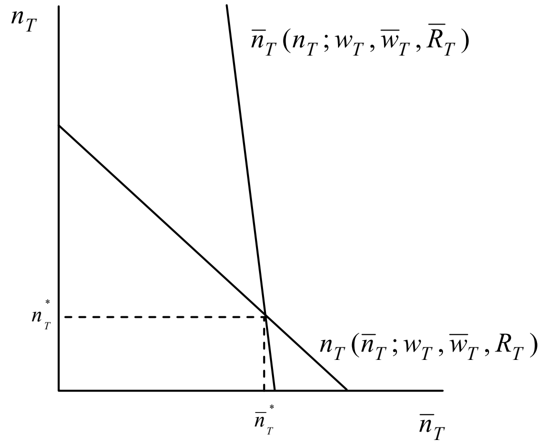

Figure 2.2
Nash equilibrium between the labour supply response functions of a husband and wife

of his/her income to the other), the labor supply functions that arise are:[12]

$$n_T^{M*} = \frac{\overline{\lambda}}{\lambda + \overline{\lambda} - 1}\left(\frac{1}{\delta} - \frac{1}{\lambda w_T}\left(\frac{1-\overline{\lambda}}{\delta}\overline{w}_T + \frac{2\overline{\lambda}-1}{\overline{\lambda}}R_T\right)\right); \tag{2.16}$$

$$\overline{n}_T^{M*} = \frac{\lambda}{\lambda + \overline{\lambda} - 1}\left(\frac{1}{\delta} - \frac{1}{\overline{\lambda}\overline{w}_T}\left(\frac{1-\lambda}{\delta}w_T + \frac{2\lambda-1}{\lambda}\overline{R}_T\right)\right). \tag{2.17}$$

To examine this equilibrium, Figure 2.2 plots Equations 2.14 and 2.15 together in $(n, \overline{n})$ space. Note that the wife's labor supply response function is linear in $\overline{n}$ and *vice versa*. The slope of the husband's curve is $-\overline{\lambda}\overline{w}/(1-\lambda)w$, while the slope of his wife's curve is $-(1-\overline{\lambda})\overline{w}/\lambda w$. Figure 2.2 is drawn to illustrate the common case where λ is close to one and $\overline{\lambda}$ is significantly less than one, *i.e.* the husband transfers a greater fraction of his income to his wife than he receives of her income. In this case, the husband's labor supply response curve is nearly vertical, while the wife's slopes downward somewhat.

Together, Equations 2.16 and 2.17 yield the following indirect utility function for a married woman in period *T*:

[12] Equations 16 and 17 make use of the fact that $R_T = \overline{R}_T$.

$$V_T^M(w_t,\overline{w}_t,\overline{n}_t,R_t,\overline{R}_t)=\ln(\frac{\lambda w_T}{\delta})+2\delta-\frac{\lambda\overline{\lambda}}{\lambda+\overline{\lambda}-1}(2-\frac{1}{\lambda w_T}((1-\overline{\lambda})\overline{w}_T$$
$$+\frac{2\overline{\lambda}-1}{\overline{\lambda}}\delta R_T)-\frac{1}{\overline{\lambda}\overline{w}_T}((1-\lambda)w_T+\frac{2\lambda-1}{\lambda}\delta\overline{R}_T)). \quad (2.18)$$

c. Solution in earlier periods

In periods $t < T$, a person's utility maximization problem depends on the expected future utility in different marital states, as well as the probability of being in those states. For example, an unmarried woman in period $T-1$ faces the following problem:

$$V_{T-1}^U(w_{T-1},R_{T-1})\equiv \max_{n_{T-1}}\{\ln(w_{T-1}n_{T-1}+R_{T-1})+\delta(1-n_{T-1})$$
$$+\beta(\eta_{T-1}E_{T-1}V_T^M(w_T,\overline{w}_T,\overline{n}_T,\frac{R_T+\overline{R}_T}{2})+(1-\eta_{T-1})E_{T-1}V_T^U(w_T,R_T))\}, \quad (2.19)$$

subject to:

$$\ln w_T=(1-\rho)\ln w_{T-1}+\theta n_{T-1}; \quad (2.20)$$

$$R_T=(1+r)R_{T-1}; \quad (2.21)$$

There is no closed form solution to this problem, hence my approach is to replace V_T^M and V_T^U with first-order Taylor series approximations in $\ln w_T$, $\ln\overline{w}_T$, R_T and $\overline{R}_T$ around the mean values, $\hat{w}$, $\hat{\overline{w}}$, $\hat{R}$ and $\hat{\overline{R}}$:

$$V_T^U(w_T,R_T)=\varsigma_T^U+(1-\frac{\delta\hat{R}}{\hat{w}})\ln w_T+\frac{\delta}{\hat{w}}R_T; \quad (2.22)$$

$$V_T^M(w_T,\overline{w}_T,R_T,\overline{R}_T)=\varsigma_T^M+(1-\frac{\lambda\overline{\lambda}}{\lambda+\overline{\lambda}-1}(\frac{1}{\lambda\hat{w}}((1-\overline{\lambda})\hat{\overline{w}}+\frac{2\overline{\lambda}-1}{\overline{\lambda}}\delta\hat{R})$$
$$-\frac{(1-\lambda)\hat{w}}{\overline{\lambda}\hat{\overline{w}}}))\ln w_T+\frac{\lambda\overline{\lambda}}{\lambda+\overline{\lambda}-1}(\frac{1}{\overline{\lambda}\hat{\overline{w}}}((1-\lambda)\hat{w}+\frac{2\lambda-1}{\lambda}\delta\hat{\overline{R}})-\frac{(1-\overline{\lambda})\hat{\overline{w}}}{\lambda\hat{w}})\ln\overline{w}_T$$
$$+\frac{\delta}{\lambda+\overline{\lambda}-1}\frac{2\overline{\lambda}-1}{\hat{w}}R_T+\frac{\delta}{\lambda+\overline{\lambda}-1}\frac{2\lambda-1}{\hat{\overline{w}}}\overline{R}_T, \quad (2.23)$$

where:

$$\varsigma_T^U\equiv-\ln\delta+\delta-1+\frac{\delta\hat{R}}{\hat{w}}\ln\hat{w}; \quad (2.24)$$

$$\varsigma_T^M \equiv \ln\frac{\lambda}{\delta}+2\delta-\frac{\lambda\bar{\lambda}}{\lambda+\bar{\lambda}-1}(2-\frac{(1-\bar{\lambda})\hat{\bar{w}}}{\lambda\hat{w}}-\frac{(1-\lambda)\hat{w}}{\bar{\lambda}\hat{\bar{w}}}$$
$$+(\frac{1}{\lambda\hat{w}}((1-\bar{\lambda})\hat{\bar{w}}+\frac{2\bar{\lambda}-1}{\bar{\lambda}}\delta\hat{R})-\frac{(1-\lambda)\hat{w}}{\bar{\lambda}\hat{\bar{w}}})\ln\hat{w}$$
$$+(\frac{1}{\bar{\lambda}\hat{\bar{w}}}((1-\lambda)\hat{w}+\frac{2\lambda-1}{\lambda}\delta\hat{\bar{R}})-\frac{(1-\bar{\lambda})\hat{\bar{w}}}{\lambda\hat{w}})\ln\hat{\bar{w}}). \quad (2.25)$$

I will assume that $E_t \ln \bar{w}_{t+1}$ and $E_t \bar{R}_{t+1}$ are uncorrelated with n_t, $\forall t$. In other words, a single woman cannot influence the income distribution of her potential husbands by her work decisions. Substituting Equations 2.20-2.23 into Equation 2.19 and solving for n then yields:

$$n_{T-1}^{U*} = \frac{1}{\delta-\varphi_{T-1}}-\frac{R_{T-1}}{w_{T-1}}, \quad (2.26)$$

where:

$$\varphi_{T-1} \equiv \beta\theta(\eta_{T-1}(1-\frac{\lambda\bar{\lambda}}{\lambda+\bar{\lambda}-1}(\frac{1}{\lambda\hat{w}}((1-\bar{\lambda})\hat{\bar{w}}+\frac{2\bar{\lambda}-1}{\bar{\lambda}}\delta\hat{R})-\frac{(1-\lambda)\hat{w}}{\bar{\lambda}\hat{\bar{w}}}))$$
$$+(1-\eta_{T-1})(1-\frac{\delta\hat{R}}{\hat{w}})). \quad (2.27)$$

In a similar fashion, a married woman's problem in period $T-1$ is:

$$V_{T-1}^M(w_{T-1},R_{T-1}) \equiv \max_{n_{T-1}}\{\ln(\lambda w_{T-1}n_{T-1}+(1-\bar{\lambda})\bar{w}_{T-1}\bar{n}_{T-1}+R_{T-1})+\delta(2-n_{T-1}-\bar{n}_{T-1})$$
$$+\beta(\gamma_{T-1}E_{T-1}V_T^U(w_T,R_T))+(1-\gamma_{T-1})E_{T-1}V_T^M(w_T,\bar{w}_T,\bar{n}_T,R_T)\}, \quad (2.28)$$

subject to:

$$\ln w_T = (1-\rho)\ln w_{T-1}+\theta n_{T-1}; \quad (2.29)$$

$$\ln \bar{w}_T = (1-\bar{\rho})\ln \bar{w}_{T-1}+\bar{\theta}\bar{n}_{T-1}; \quad (2.30)$$

$$R_T = (1+r)R_{T-1}; \quad (2.31)$$

$$\bar{R}_T = (1+r)\bar{R}_{T-1}. \quad (2.32)$$

Once again, I approximate the period T indirect utility functions with Equations 2.22 and 23.[13] This produces the following labor supply response function:

[13] Note that here V_T^M is known with certainty.

$$n_{T-1} = \frac{1}{\delta - \phi_{T-1}} - \frac{(1-\bar{\lambda})\bar{w}_{T-1}\bar{n}_{T-1} + R_{T-1}}{\lambda w_{T-1}}, \tag{2.33}$$

and, for a Nash equilibrium in the period T-1 subgame, the following labor supply function:

$$n_{T-1}^{M*} = \frac{\lambda\bar{\lambda}}{\lambda + \bar{\lambda} - 1}\left(\frac{1}{\delta - \phi_{T-1}} - \frac{1}{\lambda w_{T-1}}\left(\frac{1-\bar{\lambda}}{\delta - \bar{\phi}_{T-1}}\bar{w}_{T-1} + \frac{2\bar{\lambda}-1}{\bar{\lambda}}R_{T-1}\right)\right), \tag{2.34}$$

where:

$$\phi_{T-1} \equiv \beta\theta((1-\gamma_{T-1})(1 - \frac{\lambda\bar{\lambda}}{\lambda + \bar{\lambda} - 1}(\frac{1}{\lambda\hat{w}}((1-\bar{\lambda})\hat{\bar{w}} + \frac{2\bar{\lambda}-1}{\bar{\lambda}}\delta\hat{R}) - \frac{(1-\lambda)\hat{w}}{\bar{\lambda}\hat{\bar{w}}})) + \gamma_{T-1}(1 - \frac{\delta\hat{R}}{\hat{w}})); \tag{2.35}$$

$$\bar{\phi}_{T-1} \equiv \beta\theta((1-\gamma_{T-1})(1 - \frac{\lambda\bar{\lambda}}{\lambda + \bar{\lambda} - 1}(\frac{1}{\bar{\lambda}\hat{\bar{w}}}((1-\lambda)\hat{w} + \frac{2\lambda-1}{\lambda}\delta\hat{\bar{R}}) - \frac{(1-\bar{\lambda})\hat{\bar{w}}}{\lambda\hat{w}})) + \gamma_{T-1}(1 - \frac{\delta\hat{\bar{R}}}{\hat{\bar{w}}})). \tag{2.36}$$

Continuing to solve the problem in this recursive fashion, I can derive labor supply functions for every period. The general form for a single woman's labor supply function is:

$$n_t^{U*} = \frac{1}{\delta - \varphi_t} - \frac{R_t}{w_t}, \tag{2.37}$$

and the general forms for a married woman's labor supply response function and labor supply function are, respectively:

$$n_t = \frac{1}{\delta - \phi_t} - \frac{(1-\bar{\lambda})\bar{w}_t\bar{n}_t + R_t}{\lambda w_t}, \tag{2.38}$$

$$n_t^{M*} = \frac{\lambda\bar{\lambda}}{\lambda + \bar{\lambda} - 1}\left(\frac{1}{\delta - \phi_t} - \frac{1}{\lambda w_t}\left(\frac{1-\bar{\lambda}}{\delta - \bar{\phi}_t}\bar{w}_t + \frac{2\bar{\lambda}-1}{\bar{\lambda}}R_t\right)\right), \tag{2.39}$$

where:

$$\varphi_t \equiv \begin{cases} 0 & \text{if } t = T \\ \beta(\eta_t v_{t+1}^M + (1-\eta_t)v_{t+1}^U) & \text{if } t < T \end{cases}; \tag{2.40}$$

$$\phi_t \equiv \begin{cases} 0 & \text{if } t = T \\ \beta((1-\gamma_t)v_{t+1}^M + \gamma_t v_{t+1}^U) & \text{if } t < T \end{cases}; \tag{2.41}$$

$$v_{t+1}^{M} \equiv \frac{\partial E_t V_{t+1}^{M}}{\partial n_t} = 1 - \frac{\lambda\overline{\lambda}\delta}{\lambda+\overline{\lambda}-1}\Big(\frac{1}{\lambda\hat{w}}\Big(\frac{1-\overline{\lambda}}{\delta-\overline{\phi}_{t+1}}\hat{\overline{w}} + \frac{2\overline{\lambda}-1}{\overline{\lambda}}\hat{R}\Big)$$

$$- \frac{1}{\delta-\phi_{t+1}}\frac{(1-\lambda)\hat{w}}{\overline{\lambda}\hat{\overline{w}}}\Big) + \frac{(1-\rho)\phi_{t+1}}{\theta}; \quad (2.42)$$

$$v_{t+1}^{U} \equiv \frac{\partial E_t V_{t+1}^{U}}{\partial n_t} = 1 - \delta\frac{\hat{R}}{\hat{w}} + \frac{(1-\rho)\varphi_{t+1}}{\theta}. \quad (2.43)$$

d. Interpreting the solution

Equations 2.19 and 2.28 reveal that there are three components to a person's lifetime utility, as evaluated at any period $t < T$: the utility derived from one's current earnings, the utility from contemporaneous consumption of the household good and discounted expected future utility. δ represents a person's marginal utility from an hour of household production, whereas φ_t and ϕ_t represent the marginal future utility with respect to n_t for people in different marital states. φ_t and ϕ_t are time varying because the number of future periods varies and because γ and η change over time. I impose the constraints $\varphi_t < \delta$ and $\phi_t < \delta$, $\forall t$, which ensures that a married or unmarried person will work in a given period only if the prevailing wage is above some positive reservation wage. If $\varphi_t > \delta$ or $\phi_t > \delta$ then the person would choose to work the maximum number of hours in that period even if the wage was zero, because the marginal discounted future utility of an additional hour of work outweighed the marginal disutility of a one less hour of household production.

The labor supply functions embodied in Equations 2.37 and 2.39 represent two rectangular hyperbolas in (n, w) space. So long as $\overline{w}_t > w_t$ and $\overline{w}_t > 2\delta R_t$ then n_t^{M*} is less curved than n_t^{U*}. If, in addition, η and γ are both less than ½ then the horizontal asymptote for n_t^{M*} is greater than the asymptote for n_t^{U*}. In this case, there is a threshold wage, below which married women work less than unmarried women, but above which the reverse is true, as depicted in Figure 2.3. This illustrates intra-

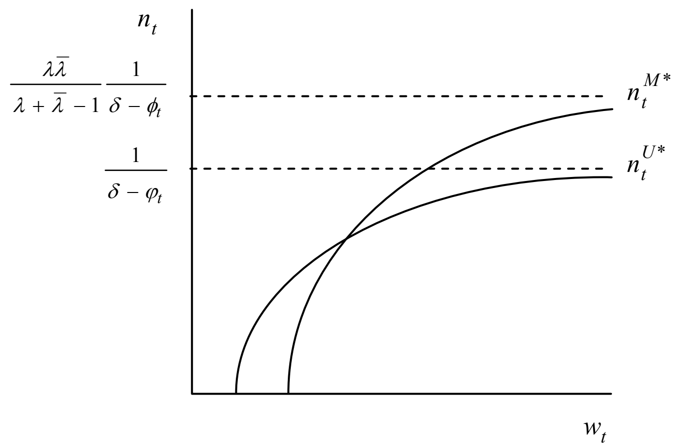

Figure 2.3
Labour supply functions of married and single persons

household specialization: a married person with a high wage works more than an otherwise-identical single person, but a low-paid married person works less and engages in household production instead.

e. Comparative statics

I wish to examine the impact of the risk of marriage and divorce on labor supply, given the framework discussed above. Consider the derivatives of Equations 2.37 and 2.39 with respect to η_t and γ_t, respectively:

$$\frac{\partial n_t^{U*}}{\partial \eta_t} = \frac{\beta}{(\delta-\varphi_t)^2}(v_{t+1}^M - v_{t+1}^U); \tag{2.44}$$

$$\frac{\partial n_t^{M*}}{\partial \gamma_t} = \frac{\lambda\bar{\lambda}\beta}{\lambda+\bar{\lambda}-1}\left(\frac{v_{t+1}^U - v_{t+1}^M}{(\delta-\phi_t)^2} - \frac{(1-\bar{\lambda})\overline{w}_t}{\lambda w_t}\frac{\bar{v}_{t+1}^U - \bar{v}_{t+1}^M}{(\delta-\bar{\phi}_t)^2}\right). \tag{2.45}$$

Equation 2.44 states that a unmarried woman will decrease her work hours in response to an increase in the likelihood of marriage if an extra hour of work would increase her expected utility more if she married than if she remained single and *vice versa*. The situation for married women is slightly more complicated. Equation 2.45

states that an increase in the probability of divorce will increase a married woman's labor supply if her marginal future utility with respect to work hours is greater when unmarried than married *and* her husband's marginal future utility with respect to hours is greater when married than unmarried. In Appendix 1, I prove by induction that so long as $\overline{w}_t > w_t + R_t$ and $\delta < 1$ then $v^U_{t+1} > v^M_{t+1}$ and $\overline{v}^M_{t+1} > \overline{v}^U_{t+1}$, $\forall t$. This means that the derivatives in Equations 2.44 and 2.45 are unambiguously negative and positive, respectively.

Note that hours of work are also influenced by the expected marital transition probabilities in all future periods. This means, for example, that single people determine their labor supply taking into account the future likelihood of divorce. The one-period-ahead recurrence derivatives in this sense are:

$$\frac{\partial n_t^{U*}}{\partial E_t \gamma_{t+1}} = \frac{\beta^2\theta^2\eta_t}{(\delta-\varphi_t)^2}((\frac{\lambda\overline{\lambda}\delta}{\lambda+\overline{\lambda}-1}\frac{(1-\lambda)\hat{w}}{\overline{\lambda}\hat{\overline{w}}}\frac{1}{(\delta-\phi_{t+1})^2}+\frac{1-\rho}{\theta})(v^U_{t+2}-v^M_{t+2})$$
$$-\frac{\lambda\overline{\lambda}\delta}{\lambda+\overline{\lambda}-1}\frac{(1-\overline{\lambda})\hat{\overline{w}}}{\lambda\hat{w}}\frac{1}{(\delta-\overline{\phi}_{t+1})^2}(\overline{v}^U_{t+2}-\overline{v}^M_{t+2}))>0; \quad (2.46)$$

$$\frac{\partial n_t^{M*}}{\partial E_t \eta_{t+1}} = \frac{\beta^2\theta^2\gamma_t}{(\delta-\phi_t)^2}\frac{\lambda\overline{\lambda}}{\lambda+\overline{\lambda}-1}\frac{1-\rho}{\theta}(v^M_{t+2}-v^U_{t+2})<0. \quad (2.47)$$

Hence, *ceteris paribus*, single people will work more when their future divorce probabilities are high and married people will work less when their remarriage probabilities are high.

f. Extensions to the model

An obvious omission of the model described above is the treatment of children. Married women may choose to stay out of the labor market not because they are less productive in paid work than their husbands but because they wish to raise a family. This could be incorporated into the model in a simple manner by modifying the utility function, Equation 2.2, to allow men and women to have different productivities in home production, as follows:

$$u(w_t, n_t, \overline{w}_t, \overline{n}_t, R_t) = \ln(\lambda w_t n_t + (1-\overline{\lambda})\overline{w}_t \overline{n}_t + R_t) + \delta(2 - \alpha n_t - \overline{\alpha n}_t), \quad (2.48)$$

where α and $\overline{\alpha}$ are the maximum amounts of the household good that the wife and husband could produce, respectively. If one treats child-rearing as a component of the household public good, then one might assume that $\alpha > 1 \geq \overline{\alpha}$. In this case, the above analysis will hold, except that δ is replaced in the labor supply functions with $\alpha\delta$ or $\overline{\alpha}\delta$ where appropriate. This means that both married and unmarried women will work less than under the assumption of equal home productivity.

Another unrealistic assumption of the model is that the marital transition probabilities are exogenous, when they are likely to be functions of the chosen hours of work. This will be an important consideration in the empirical analysis in Section 4. The above model can be modified so that the transition probabilities are functions of the hours in all previous periods:

$$\gamma_t = \gamma(n_1, ..., n_{t-1}); \quad (2.49)$$

$$\eta_t = \eta(n_1, ..., n_{t-1}). \quad (2.50)$$

In this case, the key derivatives in Equations 2.44 and 2.45 will be unchanged, although the derivative of hours with respect to future transition probabilities will be altered. The fully endogenous case where γ_t and η_t are functions of contemporaneous work hours is more complicated and may give rise to multiple equilibria.[14]

3. Data

The empirical analysis uses data for 1979-2004 from the NLSY 1979, which is a nationally representative sample of 12,686 young men and women who were 14-22 years old when they were first surveyed in 1979. These individuals were interviewed

[14] One could imagine a scenario where there is a low *n*/low γ equilibrium and a high *n*/high γ equilibrium.

annually until 1994 and are currently interviewed on a biennial basis.[15] Like Ahituv and Lerman (2005), I dropped the military over-sample and the low-income white over-sample, which were discontinued in 1986 and 1991, respectively, and together comprise 2,923 individuals. This left a sample of 4,837 males and 4,926 females, containing 54,481 male person-year observations and 58,764 female person-year observations.

The NLSY questionnaire contains detailed information on the timing of past changes in marital status, allowing the creation of a complete marital history for each person. I consider four marital states: never married, married for the first time, remarried and divorced or separated.[16]

The annual earnings and hours worked by a respondent and his/her spouse during the year prior to each interview are available and a wage variable was constructed from these. For those who did not work in a given year, had missing income or work hours data, received self-employment income or had a wage less than $2 or greater than $200, I interpolated a wage rate using information on the person's wage rate in previous and future periods. For observations that could not be interpolated, I inserted the nearest valid observation.[17] All monetary values are expressed in 2000 dollars, using the National Income and Product Account price index for personal consumption expenditures.

Other variables that are used in the labor supply regressions include race/ethnicity;

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[15] Ahituv and Lerman (2005) were able to construct an annual panel, using the retrospective information that was provided by respondents after the switch to biennial surveys. Although this allows the construction of complete marital status, work hours and wage series, it is not possible to recover spousal characteristics for the missing years.

[16] Separation is grouped with divorce as the predictions discussed in the previous section are driven by the division of labor within a shared household, not any legal definition of marriage. Separations that last less than a year are ignored in the hazard models in Section 4.

[17] Imputing missing wage observations using ordinary least squares and fixed effects regression models instead made little difference to the results presented in the following section.

age; highest schooling grade completed; percentile score on the Armed Forces Qualification Test (AFQT); family rent, dividend and interest income; region of residence; urban status; whether the respondent was born in a foreign country; whether the respondent's health limited the amount of work he/she could perform; number of children in household and presence of a child aged under 6 in the household; and the local unemployment rate. In addition, an index measuring attitudes towards the roles of men and women is constructed from eight questions asked of the respondent during the 1982 interview using factor analysis.[18]

Additional variables that are used in the marital transition equations are current religion of the respondent and whether he/she attends religious services weekly; whether the respondent's parents separated before age 18; the age a respondent expects to get married for the first time, as asked in 1979; actual age at marriage and whether the respondent had a child present in the household at the time of marriage.

Means for some of the key variables used in the labor supply regressions are presented in Table 2.1, including the marital transition hazard rates, which will be described in the next section. Each observation here represents a person-year combination and the sample is restricted to ages 25 and above. Note that the male sample features a considerably higher percentage of never-married observations. This is because women tend to marry for the first time at younger ages than men.

[18] The statements the respondents were asked to evaluate on a four-point scale were: "a woman's place is in the home, not in the office or shop", "a wife who carries out her full family responsibilities doesn't have time for outside employment", "a working wife feels more useful than one who doesn't hold a job", "employment of wives leads to more juvenile delinquency", "employment of both parents is necessary to keep up with the high cost of living", "it is much better for everyone concerned if the man is the achiever outside the home and the woman takes care of the home and family", "men should share the work around the house with women, such as doing dishes, cleaning and so forth" and "women are much happier if they stay at home and take care of their children".

Table 2.1
Means for the labour supply equation estimation sample

Variable	Females	Males
Annual hours of work	1512.711	2154.311
Employed	0.848	0.968
Never married	0.258	0.374
First marriage	0.534	0.502
Subsequent marriage	0.051	0.027
Divorced	0.157	0.097
Wage	13.105	16.699
Spouse wage	20.531	13.914
Non-wage income (in 1000s)	1.274	3.289
Age	31.004	30.595
Black non-Hispanic	0.146	0.129
Hispanic	0.055	0.057
Highest grade completed	14.006	13.760
AFQT score	50.210	52.417
Foreign born	0.035	0.038
Midwest	0.289	0.331
South	0.348	0.315
West	0.169	0.173
Urban	0.816	0.806
Local unemployment rate	0.066	0.067
Number of children	1.237	0.847
Child under 6	0.416	0.347
First marriage hazard	0.070	0.070
First divorce hazard	0.011	0.006
Subsequent marriage hazard	0.045	0.043
Subsequent divorce hazard	0.002	0.000
Number of observations	25,552	22,851

Notes: Means are calculated using the 1979 sampling weights.
Wages and incomes are in constant (2000) dollar values, using the personal consumption expenditures price index from the National Income and Product Accounts.

4. Approach and results

The primary analysis is concerned with estimating labor supply functions for married and unmarried individuals, controlling for the probability of exiting one's current marital state. To facilitate estimation, I linearize Equations 2.37 and 2.39 in $\ln w_t$, $\ln \overline{w}_t$, R_t, $\overline{R}_t$, η_t and γ_t and combine them in a single expression. To allow for heterogeneity among individuals, *i*, I also condition on demographic factors, **X**, and introduce an error term, ε:

$$n_{it} = \chi_{0j} + \chi_{1j} \ln w_{it} + \chi_{2j} \ln \overline{w}_{it} + \chi_{3j} R_{it} + \chi_{4j} \eta_{it} + \chi_{5j} \gamma_{it} + \mathbf{X}_{it} \boldsymbol{\pi}_j + \varepsilon_{it}; \qquad (2.51)$$

$$\overline{n}_{it} = \overline{\chi}_{0j} + \overline{\chi}_{1j} \ln \overline{w}_{it} + \overline{\chi}_{2j} \ln w_{it} + \overline{\chi}_{3j} \overline{R}_{it} + \overline{\chi}_{4j} \eta_{it} + \overline{\chi}_{5j} \gamma_{it} + \overline{\mathbf{X}}_{it} \overline{\boldsymbol{\pi}}_j + \overline{\varepsilon}_{it} . \qquad (2.52)$$

The linearized coefficients for women are:

$$\chi_{0j} \equiv I_j \Big(\frac{1}{\delta - \hat{\phi}} - \frac{(1-\overline{\lambda})\hat{\overline{w}}}{\lambda \hat{w}} \Big(\frac{1}{\delta - \hat{\overline{\phi}}}\Big) - \Big(\frac{(1-\overline{\lambda})\hat{\overline{w}}\hat{\overline{n}} + \hat{R}}{\lambda \hat{w}} + \frac{(1-\lambda)(1-\overline{\lambda})\hat{n}}{\lambda \overline{\lambda}}\Big) \ln \hat{w}$$

$$+ \Big(\frac{(1-\overline{\lambda})\hat{\overline{w}}\hat{\overline{n}}}{\lambda \hat{w}} + \frac{(1-\overline{\lambda})((1-\lambda)\hat{w}\hat{n} + \hat{\overline{R}})}{\lambda \overline{\lambda} \hat{w}}\Big) \ln \hat{\overline{w}}\Big) + (1 - I_j)\Big(\frac{1}{\delta - \hat{\varphi}} - \frac{\hat{R}}{\hat{w}} \ln \hat{w}\Big); \qquad (2.53)$$

$$\chi_{1j} \equiv \frac{1}{\hat{w}} \Big(I_j \Big(\frac{(1-\overline{\lambda})\hat{\overline{w}}\hat{\overline{n}} + \hat{R}}{\lambda} + \frac{(1-\lambda)(1-\overline{\lambda})\hat{w}\hat{n}}{\lambda \overline{\lambda}}\Big) + (1 - I_j)\hat{R}\Big); \qquad (2.54)$$

$$\chi_{2j} \equiv -\frac{(1-\overline{\lambda})}{\lambda \hat{w}} \Big(\hat{\overline{w}}\hat{\overline{n}} + I_j \frac{(1-\lambda)\hat{w}\hat{n} + \hat{R}}{\overline{\lambda}}\Big); \qquad (2.55)$$

$$\chi_{3j} \equiv -\frac{1}{\lambda \hat{w}} \Big(1 + I_j \frac{1-\overline{\lambda}}{\overline{\lambda}}\Big); \qquad (2.56)$$

$$\chi_{4j} \equiv (1 - I_j)\beta\theta \frac{\hat{v}^M - \hat{v}^U}{(\delta - \hat{\varphi})^2}; \qquad (2.57)$$

$$\chi_{5j} \equiv I_j \beta\theta \Big(\frac{\hat{v}^U - \hat{v}^M}{(\delta - \hat{\phi})^2} - \frac{\hat{\overline{v}}^U - \hat{\overline{v}}^M}{(\delta - \hat{\overline{\phi}})^2}\Big), \qquad (2.58)$$

where j indexes marital state and I_j is an indicator function for being married. Different specifications of ε will be considered.

In all estimates of Equations 2.51 and 2.52 discussed in this section, the dependent variable is annual hours of work in the previous year. The imputed log wage and family non-wage income are included, along with their interactions with all marital states.[19] The spouse's imputed wage is interacted with first and subsequent marriage. Additional controls include education, the gender roles index, number of own children in household and whether the youngest child was under 6, which are interacted with all marital states; spouse education and the age difference between spouses, which are interacted with first and subsequent marriages; as well as race/ethnicity, AFQT score, urban status, foreign born status, health status, whether attending regular school, and

[19] Since I use *family* income, one would expect the coefficients on the interaction terms to be negative, even if the non-wage income elasticity of labor supply was the same for single and married people.

the local unemployment rate. In order to focus on those who have completed the majority of their schooling, I drop those observations before age 25.

Obviously, an individual's probability of changing marital state is unknown to the researcher. One approach is to use as a proxy the divorce rate among people with similar characteristics. The June supplement of the Current Population Survey contains information on the age of respondents at first marriage and divorce. From the 1980 supplement, I calculated the proportion of first marriages that end (by divorce or widowhood) within ten years for each combination of region, education, race/ethnicity and age at marriage category.[20] As a measure of marriage, I calculated the fraction of people who had married by the age of 30 within region, education, race/ethnicity and sex categories. Table 2.2 presents the results of using these estimates as measures of γ and η in Equations 2.51 and 2.52. Consistent with the model presented in Section 2, the divorce rate is seen to have a significant positive effect on the hours worked by women in their first marriage but an insignificant effect on hours for men. Furthermore, the marriage rate is positively associated with hours for never-married men. However, contrary to the predictions of the model, the marriage rate also has a positive impact on the hours worked by never-married women.

A problem with these measures of the marital transition probabilities is that they do not take account of the specific characteristics of each individual or married couple. Furthermore, they do not reflect the ways in which the risk of divorce evolves over the course of a marriage. Hence, the results in Table 2.2 only reflect cross-sectional differences in divorce likelihood, not inter-temporal variation. Exploiting the longitudinal nature of the NLSY, an alternative approach is to use a person's actual experience of divorce in the future. Table 2.3 reports average hours for a sample of

[20] I use three education categories (less than Grade 12, Grade 12, at least some college), three race/ethnicity categories (white non-Hispanic, black non-Hispanic and Hispanic) and three age at marriage categories (15-20, 21-25 and 26 or over).

Table 2.2
Estimates of labour supply equations using CPS divorce and marriage rates

Variable	(i) OLS Females	(ii) Tobit Females	(iii) OLS Males	(iv) Tobit Males
Never married × marriage rate	728.111***	951.490***	1109.441***	1397.441***
	(260.868)	(319.759)	(162.087)	(174.744)
First marriage × divorce rate	428.421***	475.511***	38.092	38.043
	(85.176)	(104.041)	(99.968)	(106.661)
(Pseudo) R-squared	0.159	0.013	0.155	0.010
Number of observations	35,275	35,275	31,052	33,891

Note: Controls also include own and spouse log wage, non-wage income, own and spouse highest grade completed, age difference between spouses, attitude to gender roles, number of children and child under 6, all interacted with marital status, plus age, age squared, black non-Hispanic, Hispanic, attended school, AFQT score, poor health, foreign born, 3 region dummies, urban, local unemployment rate and marital status dummies.
Standard errors are presented in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

divorcing men and women at different times before and after divorce, along with a comparison group of non-divorcing people with the same age composition. Among women who divorce, annual hours are seen to increase sharply, from 1262 three years before the separation to 1619 two years after it. Almost half of this adjustment occurs before divorce. In contrast, the comparison group works less in all periods and exhibits no pattern over time. Among divorcing men, the situation is less clear. Although there is evidence of a spike in hours immediately before and after divorce, these men both begin and end the period of analysis working less than the comparison group.

To control for other relevant factors that might vary between divorcing and non-divorcing people, Table 2.4 presents the results of estimating Equations 2.51 and 2.52 using the actual experience of changes in marital state in the following year as measures of γ and η. The results for men are consistent with predictions for all marital transitions. For women, there is evidence of increased work hours in the year prior to the dissolution of a first marriage. However, there is no evidence of decreased hours

Table 2.3
Average hours of work for divorcing and non-divorcing couples

Year relative to divorce	Females		Males	
	Divorcers	Non-divorcers	Divorcers	Non-divorcers
-3	1262	1220	1968	2077
-2	1309	1218	2067	2080
-1	1348	1220	2075	2079
0	1425	1221	2107	2084
1	1579	1219	2215	2086
2	1619	1216	2018	2073

Notes: The divorcing sample consists of those who were observed both 3 years before and 2 years after their first marriage ended.
The non-divorcing sample consists of all individuals in their first marriage who are not observed to separate and reflects the age composition of the divorcing sample at a particular year relative to divorce.
All means are weighted using the 1979 sample weights.

before first marriage and, in fact, women appear to behave similarly to men by working longer hours in the lead-up to a subsequent marriage.

As noted by previous authors, future experience of marriage and divorce are poor measures of the transition probabilities for two reasons. Firstly, at the time they make their labor supply decisions, individuals do not know with certainty that they will change marital state. More importantly, past work has found that past hours of work are important determinants of divorce, implying that the estimates in Table 2.4 will suffer from endogeneity bias. To date, no empirical research has considered marriage probabilities, however, in order to isolate the causal effect of divorce risk on labor supply, previous United States studies have proxied for the former by using probit models to estimate the probability of an individual actually becoming divorced within a specified time.[21] I take a somewhat different approach and estimate both marriage and divorce probabilities using Cox proportional hazard models. These allow non-parametric estimates of the marital transition probabilities (or hazard rates) at different

[21] Johnson and Skinner (1986) used the probability of divorce within three years, a decision which Gray (1995) and Sen (2000) both subsequently adopted.

Table 2.4
Estimates of labour supply equations using actual marriage and divorce in the following year

Variable	(i) OLS Females	(ii) Tobit Females	(iii) OLS Males	(iv) Tobit Males
Never married × marriage	103.425**	127.184***	241.023***	255.418***
	(41.832)	(49.386)	(37.060)	(39.137)
First marriage × divorce	91.579*	118.957**	-104.571**	-108.845*
	(47.468)	(56.134)	(52.713)	(55.661)
Divorced × remarriage	82.131*	117.040**	182.984***	187.726***
	(49.321)	(58.179)	(57.715)	(60.986)
Subsequent marriage × divorce	89.761	135.520	-224.305**	-241.696**
	(91.993)	(108.486)	(108.091)	(114.261)
R-squared	0.166	0.014	0.152	0.011
Number of observations	43,247	43,247	38,484	38,484

Note: Controls also include own and spouse log wage, non-wage income, own and spouse highest grade completed, age difference between spouses, attitude to gender roles, number of children and child under 6, all interacted with marital status, plus age, age squared, black non-Hispanic, Hispanic, attended school, AFQT score, poor health, foreign born, 3 region dummies, urban, local unemployment rate and marital status dummies.
Standard errors are presented in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

lengths of time in the current marital state. In contrast, previous authors have typically treated years since marriage in a parametric manner by including it as a quadratic term in the divorce probit equations.

The Cox model assumes that the hazard rate can be written as:

$$h(t,\mathbf{z}) = h_0(t)e^{\mathbf{z}\boldsymbol{\beta}}, \tag{2.59}$$

where $\boldsymbol{\beta}$ is a vector of coefficients, $\mathbf{z}$ is a vector of covariates and $h_0(t)$ is the hazard when $\mathbf{z} = \mathbf{0}$, termed the baseline hazard function. Differences in covariates result in proportional shifts of the hazard rate. An exponentiated coefficient, e^{β_i}, is referred to as a hazard ratio and its magnitude relative to 1 determines whether the covariate in question increases or decreases the hazard rate.

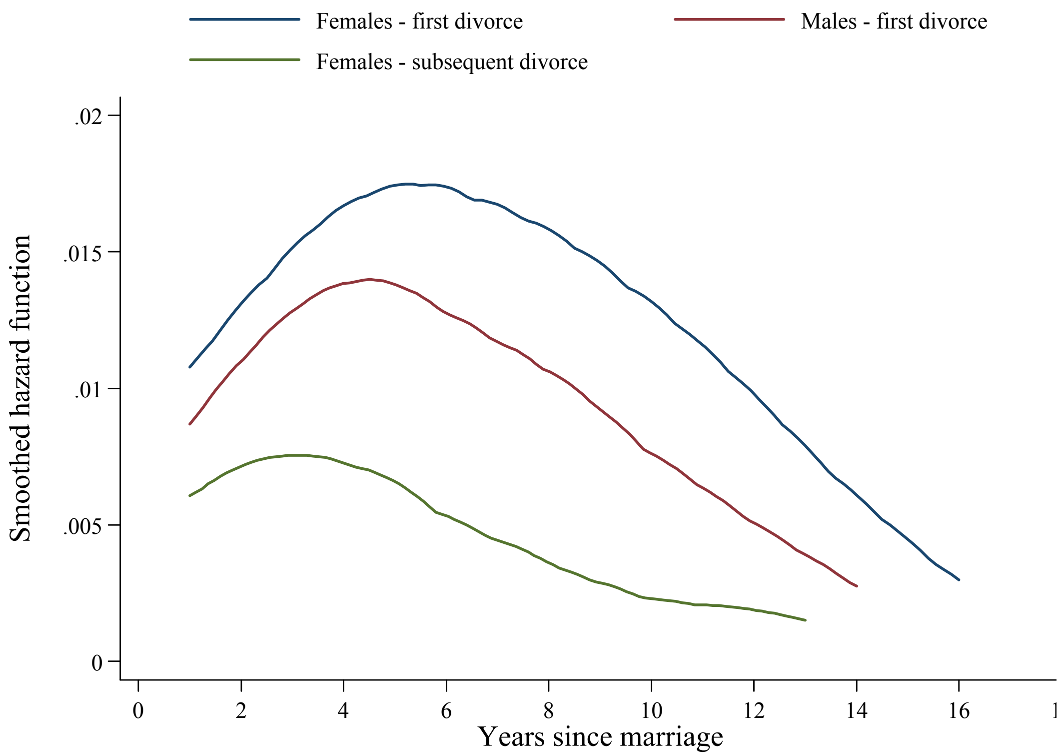
Table 2.5 presents the results of hazard models for the probability of divorce occurring among married people. The explanatory variables that are used follow previous economic and demographic studies. I estimate separate models for men and

Table 2.5
Hazard ratios from Cox proportional hazard model estimates for the probability of divorce

Variable	(i) Females – first divorce	(ii) Females – subsequent divorce	(iii) Males – first divorce	(iv) Males – subsequent divorce
Age at marriage	0.899***	0.815***	0.870***	0.691***
Age difference	1.005	0.952	1.014	1.135**
Black non-Hispanic	1.674***	2.200	1.664***	16.236***
Hispanic	1.127	0.749	0.604**	1.051
Catholic	0.637**	0.731	1.067	0.352
Baptist	0.939	0.693	1.055	0.215**
Other protestant	0.821	0.897	0.922	0.343
Frequency of religious attendance	0.805*	0.835	0.726**	0.104**
Poor health	1.142	1.591	1.534	–
Highest grade completed	0.994	0.987	0.900***	0.995
AFQT score	0.990***	0.997	0.997	0.997
Spouse income (in 1000s)	0.998	1.009**	0.992	0.958
Non-wage income (in 1000s)	0.9998	0.499	1.010	1.000
Parents divorced	1.190	0.819	1.608***	0.792
Urban	1.167	0.629	1.543**	0.489
Child present	0.957	0.399	0.573***	2.689
Child before marriage	1.520***	2.415	1.737***	0.129**
Number of observations	17,993	2,112	16,037	1,267
Number of individuals	2,125	453	2,033	314

Note: *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.
Coefficients and standard errors are presented in Table A1.
Poor health was not included in the fourth specification as none of the men who were within twelve months of their second divorce had health limitations.

women and for exit from first marriage and exit from subsequent marriages. In all cases, individuals who marry at older ages are less likely to divorce. Non-Hispanic blacks, those who attend religious services weekly and those with children in the household at time of marriage are more likely to exit first marriages. Among women in their first marriages, Catholics and those with high AFQT scores also tend to have lower divorce hazards; for men, being Hispanic, not experiencing divorce as a child, living in a metropolitan area and having dependent children in the household all reduce the chances of exiting a first marriage. These results are broadly consistent



Notes: Hazard rates are estimated by setting all independent variables equal to their means. The Epanechnikov kernel is used.

Figure 2.4
Kernel plots of average divorce hazards

with those of hazard model analyses of divorce, such as Balakrishnan *et al*. (1987) and Castro Martin and Bumpass (1989).

Figure 2.4 depicts the hazard rates for men and women in their first marriage and women in subsequent marriages, where all explanatory variables are set equal to their means. The hazard function for men in subsequent marriages is not presented as it is implausibly high, presumably because so few remarried men are observed during the sample period. The average woman is more likely to divorce than an average man who has been married for the same time. This is because the wives of the men in the NLSY sample earn more than the married women in the sample and spousal income has a

Table 2.6
Hazard ratios from Cox proportional hazard model estimates for the probability of marriage and remarriage

Variable	(i) Females – first marriage	(ii) Females – subsequent marriage	(iii) Males – first marriage	(iv) Males – subsequent marriage
Black non-Hispanic	0.532***	0.288***	0.520***	0.559**
Hispanic	0.908	1.053	0.962	1.341
Catholic	0.962	0.575***	0.789***	0.876
Baptist	1.048	0.987	0.973	1.138
Other protestant	0.948	1.051	0.867**	1.207
Frequency of religious attendance	1.134***	1.188	1.147***	1.302
Poor health	0.967	0.511*	0.925	1.028
Highest grade completed	0.931***	1.048	0.953***	1.151**
AFQT score	1.001	0.999	1.003**	0.998
Non-wage income (in 1000s)	1.012**	0.977	0.9997	0.974
Parents divorced	0.915	0.913	0.924	0.751
Urban	0.863***	0.903	0.835***	0.718
Child present	0.766***	0.558***	1.205*	1.099
Expected marriage age	0.749***	0.770***	0.819***	0.879
Number of observations	28,345	5,885	33,323	3,546
Number of individuals	3,393	1,177	3,565	823

Note: *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.
Coefficients and standard errors are presented in Table A2.

negative effect on the divorce hazard.[22] The hazard rates peak between four and five years after marriage. Remarried women are less likely to divorce than women in their first marriage.

I also estimate hazard models for entry into marriage and the results of these are presented in Table 2.6. For entry into first marriage, age 15 was chosen as the origin because the minimum legal age for marriage without a court order (but with parental consent) in most states is 16.[23] Non-Hispanic blacks are seen to be less likely to marry or remarry. More educated and less devout persons, city-dwellers and those who expected to marry later are all less likely to marry at a given age. Interestingly, the

[22] If the average incomes among married men and women in the sample are used as the spousal incomes for the opposite sex, the two first divorce lines in Figure 2.4 overlap almost exactly.

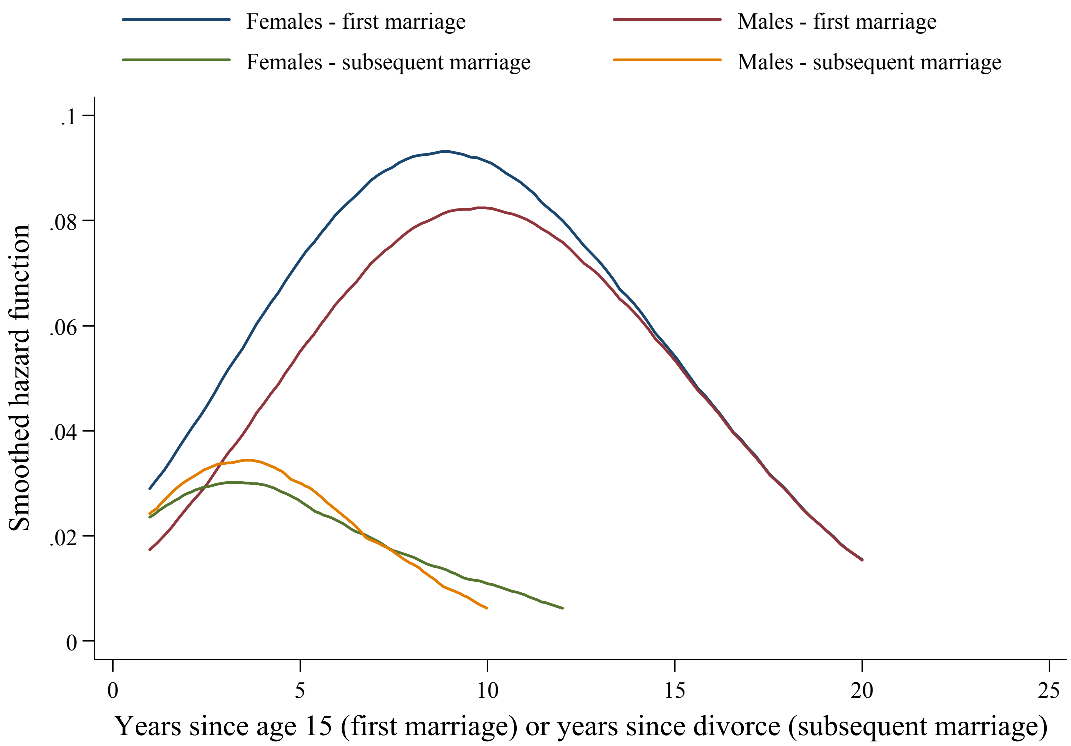
[23] 91 women and 5 men in the NLSY dataset married before age 15, which in most states would require a court order in addition to parental consent. These observations are excluded from the analysis in Table 2.3.

presence of a child in the household decreases the likelihood of a woman marrying, but *increases* the likelihood of a man marrying. Having considerable non-wage income renders a woman more likely to marry. Among men, being Catholic or Protestant other than Baptist and having a higher AFQT score are associated with a higher probability of marriage. Again, these results largely agree with those of previous studies of marriage and remarriage, such as Michael and Brandon Tuma (1985) and Koo *et al*. (1984).

The average marriage hazard functions for the four cases are plotted in Figure 2.5. Not surprisingly, women are more likely than men to marry at younger ages. The probability of marriage is highest at age 24 for women and 25 for men. The probability of remarriage peaks four years after divorce, with men being more likely to remarry rapidly.

Estimates of marriage and divorce probabilities for each person-year observation (η and γ in the model presented in Section 2) are obtained from the hazard models in Tables 2.2 and 2.3 by computing the baseline hazard and multiplying it by the exponentiated linear prediction, as in Equation 2.59. These predicted probabilities are then interacted with the appropriate marital state (never married, first marriage, divorced or subsequent marriage) and are used as regressors in labor supply regressions, as reported in Table 2.7. Other than the marital transition probabilities, the specification is the same as in Tables 2.2 and 2.4.

Ordinary least squares estimates are presented in the first and third columns of Table 2.7 and tobit estimates are reported in the second and fourth columns. Bootstrapped standard errors are computed for the marital transition probability variables, to correct for prediction error in the first-stage hazard estimates. The regular and bootstrapped standard errors are expected to form lower and upper bounds on the



Notes: Hazard rates are estimated by setting all independent variables equal to their means. The Epanechnikov kernel is used.

Figure 2.5
Kernel plots of average marriage hazards

true standard error, respectively.[24] The reported wage and non-wage income elasticities are generally as expected. Women have higher wage elasticities than men in the same marital state and the elasticities for married men are actually negative. The hours worked by a married woman are more responsive to her spouse's wage rate than is the case for a married man. Although unreported, the coefficients on the gender

[24] As Johnson and Skinner (1986) noted, since individuals do not know whether they will change marital status in the following year at the time they make their labor supply decisions, the regular standard errors are only biased to the extent that the person's subjective probability explains more than the predicted hazard rate. To that end, the regular standard errors will be correct if the individual has no more knowledge than the econometrician, while the bootstrapped standard errors will be correct if the individual has perfect knowledge of changes in marital status in the following year.

Table 2.7
Estimates of labour supply equations using estimated marriage and divorce hazard rates

Variable	(i) OLS Females	(ii) Tobit Females	(iii) OLS Males	(iv) Tobit Males
Log wage	232.331***	288.858***	8.436	22.998***
	(19.255)	(23.086)	(14.968)	(15.689)
First marriage × log wage	-134.011***	-127.967***	-263.405***	-275.269***
	(23.409)	(27.992)	(21.238)	(15.689)
Divorced × log wage	-299.806***	-324.848***	-210.226***	-214.159***
	(28.148)	(33.516)	(29.521)	(30.903)
Subsequent marriage × log wage	-359.147***	-392.550***	-656.617***	-672.271***
	(43.716)	(51.926)	(64.803)	(67.724)
First marriage × spouse log wage	-287.461***	-356.379***	56.833***	56.127***
	(15.254)	(18.300)	(15.029)	(15.669)
Subsequent marriage × spouse log wage	-111.358**	-133.309**	159.622**	165.418***
	(49.331)	(58.917)	(70.687)	(73.891)
Non-wage income (in 1000s)	-5.684	-7.089	0.076	0.079
	(3.599)	(4.198)	(0.046)	(0.048)
First marriage × non-wage income	5.585	0.605	3.672***	3.638***
	(3.600)	(4.386)	(1.026)	(1.069)
Divorced × non-wage income	0.435	-0.958	-0.042	-0.044
	(3.936)	(4.815)	(0.080)	(0.083)
Subsequent marriage × non-wage income	-25.180***	-35.874***	5.031	4.579
	(9.648)	(12.551)	(5.955)	(6.217)
First marriage	1668.640***	1919.989***	1131.001***	1204.453***
	(109.995)	(131.512)	(98.711)	(103.100)
Divorced	722.850***	777.278***	219.028*	228.647*
	(124.596)	(148.525)	(131.024)	(137.263)
Subsequent marriage	1379.896***	1518.297***	1317.643***	1355.084***
	(234.812)	(278.954)	(322.318)	(336.781)
Never married × marriage probability	3853.004***	4351.235***	2169.397***	2327.388***
	(406.330)	(481.015)	(347.241)	(362.908)
	[571.646]	[496.046]	[398.320]	[493.808]
First marriage × divorce probability	4715.265**	5549.014**	-2337.963	-2207.696
	(868.814)	(1033.088)	(1599.488)	(1670.289)
	[2389.004]	[2226.549]	[2521.332]	[3353.317]
Divorced × remarriage probability	800.133	1007.502	460.906	521.291***
	(412.886)	(485.436)	(664.842)	(694.478)
	[891.338]	[1122.255]	[1643.534]	[1394.518]
Subsequent marriage × divorce probability	-12549.440	-16737.690	7.18×10^6	7.12×10^6
	(9531.438)	(11553.330)	(5.13×10^6)	(5.53×10^6)
	[7.05×10^6]	[4.48×10^5]	[5.67×10^{11}]	[1.10×10^9]
(Pseudo) R-squared	0.208	0.017	0.151	0.011
Number of observations	25,552	25,552	22,851	22,851

Notes: Controls also include own and spouse highest grade completed, age difference between spouses, attitude to gender roles, number of children and child under 6, all interacted with marital status, plus age, age squared, black non-Hispanic, Hispanic, attended school, AFQT score, poor health, foreign born, 3 region dummies, urban, local unemployment rate and marital status dummies. Standard errors are presented in parentheses and bootstrapped standard errors in brackets. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, and refer to the bootstrap distribution where it is reported.

roles attitude variables indicate that conservative women tend to work less than other women in all marital states, however conservative men also have slightly lower hours before and during first marriage, compared to other men.

Consistent with the predictions of the theory, higher probabilities of divorce are found to increase the hours worked by women in their first marriage, but to decrease the hours worked by men, although the latter relationship is statistically insignificant. Higher probabilities of first marriage are associated with more work hours among both men and women. The latter result is somewhat puzzling. One possible explanation is that a woman's marginal utility with respect to her hours is not constant over the life-cycle but rather is higher when divorced than when never married. The transition probabilities for those who have been divorced at least once are insignificant. As mentioned above, this may be because there are relatively few observations in divorced or remarried states or because after experiencing one divorce, people become less responsive to further changes in marital transition probabilities.

Unlike all previous studies, since I have a full panel for all individuals over the sample period, as they move between marital states, I can also employ panel data models. The first and third columns of Table 2.8 report the results of applying a fixed effects, or within, estimator to Equations 2.51 and 2.52, which controls for all unobserved time-invariant determinants of labor supply. The marriage probability continues to have a positive effect on hours for both sexes, as does the divorce probability for women.[25] These estimates imply that married women allocate labor supply optimally over their lifetimes in response to changes in probability of marital dissolution. The second and fourth columns of Table 2.8 give the results from the between estimator, whereby the observations are averaged over all periods for each individual. There is evidence that women from high divorce risk groups work more

[25] A Hausman test rejected the hypothesis that a random effects estimator is consistent.

Table 2.8
Within and between estimates of labour supply equations using estimated marriage and divorce hazard rates

Variable	(i) Within Females	(ii) Between Females	(iii) Within Males	(iv) Between Males
Never married × marriage probability	647.993 (458.777) [476.179]	4393.990*** (1062.648) [844.922]	2114.120*** (389.467) [490.4969]	2461.066*** (939.086) [1035.315]
First marriage × divorce probability	2272.232 (1030.905) [1797.585]	7293.940*** (2134.298) [2549.522]	3573.985 (2335.473) [2342.904]	-3578.060 (3538.877) [2680.563]
Divorced × remarriage probability	401.439 (459.915) [959.295]	432.944 (844.118) [1174.655]	839.556 (663.519) [1452.954]	1850.282 (1445.243) [2774.321]
Subsequent marriage × divorce probability	-20496.950 (12649.300) [1.43×10^6]	-32659.990 (16047.020) [3.52×10^6]	1.01×10^7 (6.17×10^6) [3.54×10^{11}]	-1.90×10^6 (9.01×10^6) [2.59×10^{11}]
R-squared	0.534	0.383	0.480	0.286
Number of observations	25,552	25,552	22,851	23,963

Notes: Controls also include own and spouse log wage, non-wage income, own and spouse highest grade completed, age difference between spouses, attitude to gender roles, number of children and child under 6, all interacted with marital status, plus age, age squared, black non-Hispanic, Hispanic, attended school, AFQT score, poor health, foreign born, 3 region dummies, urban, local unemployment rate and marital status dummies.
Standard errors are presented in parentheses and bootstrapped standard errors in brackets. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, and refer to the bootstrap distribution where it is reported.

over the entire duration of their marriages, regardless of the specific danger of their own relationship ending. This casts doubt on the approach of Johnson and Skinner (1988), who analyzed the reasons behind labor supply increases by women after divorce by comparing hours two and three years prior to separation and one and two years afterwards.

The identification of the coefficients on the marriage and divorce probabilities in Tables 2.7 and 2.8 depends crucially on the exclusion of variables from the labor supply equation that are relevant to the likelihood of marriage or divorce occurring.[26] Given the absence of any clearly exogenous shocks to the marriage and divorce

[26] Technically, the non-linear nature of Cox proportional hazard model is sufficient to identify the labor supply equation.

Table 2.9
Estimates of labour supply equations using marital happiness variable

Variable	(i) Tobit Females	(ii) Within Females	(iii) Tobit with lags Females	(iv) Within with lags Females
First marriage × happy with marriage	-56.811* (30.459)	-37.418 (28.007)	-92.178*** (31.475)	-120.964*** (28.464)
First marriage × unhappy with marriage	120.970 (81.380)	69.710 (63.801)	191.032** (85.995)	70.554 (68.040)
(Pseudo) R-squared	0.012	0.468	0.012	0.487
Number of observations	21,946	21,946	18,423	18,423

Notes: Controls also include own and spouse log wage, non-wage income, own and spouse highest grade completed, age difference between spouses, attitude to gender roles, number of children and child under 6, all interacted with marital status, plus age, age squared, black non-Hispanic, Hispanic, attended school, AFQT score, poor health, foreign born, 3 region dummies, urban, local unemployment rate and marital status dummies.
Standard errors are presented in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

equations, there is a risk that some of these variables have an independent effect on labor supply. For example, Heineck (2004) found that strongly religious married women tend to work less than other married women in Germany. An alternative approach that has not been considered previously is to rely on a respondent's own evaluation of the state of his/her marriage. This has two advantages over the use of predicted divorce. Firstly, it allows the identification of individuals who anticipate divorces that never transpire and *vice versa*. Secondly, if satisfaction with marriage is evaluated in the same period as hours, it circumvents the problem of reverse causality encountered when using divorce in the future as a measure of divorce risk. However, estimates may still be susceptible to endogeneity bias if marital satisfaction and work hours are jointly determined by unobserved variables.

The NLSY includes questions on whether respondents were "very happy", "fairly happy" or "not too happy" with their current marriage. Unfortunately, these were only asked of women in 1992 and 1994 onwards. Table 2.9 presents the results of estimating Equation 2.51 for these years only. The measures of divorce risk are the interaction of first marriage with a dummy for those who responded that they were "very happy" with their marriage and those who responded that they were "not too happy". The first two columns of Table 2.9 reveal that those who are unhappy with their marriage are found to work longer hours that the baseline group, whereas those who are very happy work less, however these results are only marginally significant. Once problem is that marital satisfaction is measured as of the interview date, whereas hours of work pertain to the previous calendar year, meaning that endogeneity may still be a problem. A simple solution is to use the level of marital satisfaction from two years earlier, as this should be exogenous to the current labor supply decision. The third column of Table 2.9 shows that this yields highly significant results. Those who are very happy with their marriage work 92 hours fewer than the comparison group; those who are unhappy work 191 hours more. The former result remains when individual effects are included, as seen in the final column.

Finally, it should be remembered that the labor supply equations 2.51 and 2.52 are linear approximations to the first order conditions that arise from the theoretical model. With higher order approximations, one would expect to find interactions of the marital transition probabilities with own and spouse wages. To examine this possibility, I repeat the main specifications from Table 2.7, adding the log ratio of a married woman's wage to her husband's wage as a regressor. As reported in Table 2.10, this ratio has a significant coefficient for women and a positive coefficient for men, although the former is not significant under the bootstrap distribution. These results imply that as a woman's wage increases towards parity with her husband, the risk of divorce has an increasingly small effect on her hours of work. They also suggest that divorce risk can play an important role in the work decisions of those men who earn lower wages than their wives. This finding supports the conclusions of the model presented in Section 2 insofar as it indicates that the differences in the labor

Table 2.10
Estimates of labour supply equations including the wage ratio

Variable	(i) OLS Females	(ii) Tobit Females	(iii) OLS Males	(iv) Tobit Males
Never married × marriage probability	3866.611***	4371.149***	2202.906***	2358.891***
	(406.379)	(481.052)	(347.209)	(362.865)
	[507.181]	[563.448]	[590.796]	[561.397]
First marriage × divorce probability	4120.986**	4774.081**	-3394.193	-3194.028
	(935.148)	(1107.809)	(1618.850)	(1689.947)
	[2033.541]	[1955.054]	[4574.468]	[4221.708]
Divorced × remarriage probability	805.874	1016.107	509.345	566.841
	(412.839)	(485.367)	(664.684)	(694.288)
	[1016.250]	[1321.819]	[2015.533]	[1377.602]
Subsequent marriage × divorce probability	15266.870	8626.519	1.47×10^7	1.52×10^7
	(13720.240)	(16647.000)	(6.63×10^6)	(6.91×10^6)
	[1.32×10^6]	[4.31×10^5]	[2.66×10^{11}]	[1.90×10^9]
First marriage × divorce probability × log wage ratio	-1634.365	-2155.463	7432.218***	7014.738***
	(866.219)	(1039.357)	(1798.833)	(1881.019)
	[1725.132]	[2072.967]	[2778.138]	[2770.711]
Subsequent marriage × divorce probability × log wage ratio	23122.350**	20495.020*	-2.05×10^7	-2.24×10^7
	(8206.426)	(9748.456)	(1.16×10^7)	(1.22×10^7)
	[9497.462]	[11915.820]	[1.91×10^7]	[1.88×10^7]
(Pseudo) R-squared	0.209	0.017	0.152	0.011
Number of observations	25,552	25,552	22,851	22,851

Notes: Controls also include own and spouse log wage, non-wage income, own and spouse highest grade completed, age difference between spouses, attitude to gender roles, number of children and child under 6, all interacted with marital status, plus age, age squared, black non-Hispanic, Hispanic, attended school, AFQT score, poor health, foreign born, 3 region dummies, urban, local unemployment rate and marital status dummies.
Standard errors are presented in parentheses and bootstrapped standard errors in brackets. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, and refer to the bootstrap distribution where it is reported.

supply-divorce risk relationship hinge solely on the assumption that men earn more than women, rather than any specific gender roles within the household.

5. Conclusion

For the first time, this paper has attempted to provide a theoretical framework to explain the relationship between the probability of a person changing marital state and the amount of labor he/she supplies over the life-cycle. Married couples interact in a non-cooperative fashion. Working longer hours in the labor market increases the wage a person will receive in the future, meaning that some married individuals may want to insure against the risk of divorce by devoting more time to paid work than they would otherwise do. The model predicts that labor supply will be positively related to the probability of divorce for a person who earns a lower wage than his/her spouse and *vice versa*.

I tested the predictions of this model, drawing on longitudinal data from the NLSY 1979. Marriage and divorce probabilities were estimated using Cox proportional hazard models. These were then used as explanatory variables in labor supply regressions. As expected, married women work more hours when the probability they will divorce is higher. However, this effect only seems to hold for first marriages. Never-married men and women both work more if they have a greater chance of marriage. This last finding is intriguing and will be analyzed further in future work. The link between marital transition probabilities and hours is observed both over a person's life-cycle and across individuals and persists when arguably exogenous measures of divorce risk are used. There is also some evidence that the effect of divorce risk on hours is stronger for women who earn significantly less than their husbands.

Additional research will also explicitly consider whether work hours influence divorce probabilities, *i.e.* whether there is an additional causal effect in the reverse direction. Gray (1995) and Sen (2002) found no evidence of this using NLSY 1979 data, however Johnson (2004) provided evidence suggesting that the work hours of women in the Survey of Income and Program Participation have an independent effect on the likelihood of divorce.[27]

[27] Johnson's conclusion was based on the assumption that married people are less likely to adjust their work hours in anticipation of separation rather than actual divorce.

Finally, future work will focus on the predictions of the theory, comparing the Nash equilibrium results that are generated for married couples with the Pareto efficient outcomes and determining whether these might be achieved within a cooperative bargaining framework.

APPENDIX 1

I wish to prove that if $\overline{w}_t > w_t + 2R_t$ and $\delta < 1$ then $v^U_{t+1} > v^M_{t+1}$ and $\overline{v}^M_{t+1} > \overline{v}^U_{t+1}$, $\forall t$, however, first I need to prove that $\overline{\phi}_t > \phi_t$ and $\overline{\varphi}_t > \varphi_t$, $\forall t < T$. In cases, my approach is to use proof by induction.

a. Proof that $\overline{\phi}_t > \phi_t$ and $\overline{\varphi}_t > \varphi_t$, $\forall t < T$

i. Proof that $\overline{\phi}_{T-1} > \phi_{T-1}$ and $\overline{\varphi}_{T-1} > \varphi_{T-1}$

$$\begin{aligned}\overline{\varphi}_{T-1} - \varphi_{T-1} &= \beta\theta(\eta_T \frac{\lambda\overline{\lambda}\delta}{\lambda+\overline{\lambda}-1}(\frac{1}{\lambda\hat{w}}(\frac{1-\overline{\lambda}}{\delta}\hat{\overline{w}} + \frac{2\overline{\lambda}-1}{\overline{\lambda}}\hat{R}) - \frac{1}{\overline{\lambda}\hat{\overline{w}}}(\frac{1-\lambda}{\delta}\hat{w} + \frac{2\lambda-1}{\lambda}\hat{R}) \\ &\qquad + \frac{(1-\overline{\lambda})\hat{\overline{w}}}{\delta\lambda\hat{w}} - \frac{(1-\lambda)\hat{w}}{\delta\overline{\lambda}\hat{\overline{w}}}) + (1-\eta_T)\delta\hat{R}(\frac{1}{\hat{w}} - \frac{1}{\hat{\overline{w}}})); \\ &= \beta\theta(\eta_T \frac{\lambda\overline{\lambda}\delta}{\lambda+\overline{\lambda}-1}(\frac{2(1-\overline{\lambda})\hat{\overline{w}}}{\lambda\delta\hat{w}} - \frac{2(1-\lambda)\hat{w}}{\overline{\lambda}\delta\hat{\overline{w}}} + \frac{\hat{R}}{\lambda\overline{\lambda}}(\frac{2\overline{\lambda}-1}{\hat{w}} - \frac{2\lambda-1}{\hat{\overline{w}}})) \\ &\qquad + (1-\eta_T)\delta\hat{R}(\frac{1}{\hat{w}} - \frac{1}{\hat{\overline{w}}}));\end{aligned}$$

We know:

$\frac{1}{\hat{w}} > \frac{1}{\hat{\overline{w}}}$, since $\overline{w}_t > w_t$,

and:

$$\begin{aligned}\frac{2\overline{\lambda}(1-\overline{\lambda})\hat{\overline{w}}}{\hat{w}} - \frac{2\lambda(1-\lambda)\hat{w}}{\hat{\overline{w}}} + \delta\hat{R}(\frac{2\overline{\lambda}-1}{\hat{w}} - \frac{2\lambda-1}{\hat{\overline{w}}}) &> \frac{2\overline{\lambda}(1-\overline{\lambda})\hat{\overline{w}}}{\hat{w}} - \frac{2\lambda(1-\lambda)\hat{w}}{\hat{\overline{w}}} \\ &\qquad + \frac{\delta(\hat{\overline{w}} - \hat{w})}{\hat{\overline{w}}}(\overline{\lambda} - \lambda);\end{aligned}$$

> 0, as above.

Hence:

$\overline{\varphi}_{T-1} - \varphi_{T-1} > 0$.

Similarly, $\overline{\phi}_{T-1} > \phi_{T-1}$.

ii. Proof that $\overline{\phi}_{t+1} > \phi_{t+1}$ and $\overline{\varphi}_{t+1} > \varphi_{t+1}$ imply that $\overline{\phi}_t > \phi_t$ and $\overline{\varphi}_t > \varphi_t$

$$\overline{\varphi}_t - \varphi_t = \beta\theta(\eta_t \frac{\delta}{\lambda+\overline{\lambda}-1}(\frac{2\overline{\lambda}(1-\overline{\lambda})\hat{\overline{w}}}{(\delta-\overline{\phi}_{t+1})\hat{w}} - \frac{2\lambda(1-\lambda)\hat{w}}{(\delta-\phi_{t+1})\hat{\overline{w}}} + \hat{R}(\frac{2\overline{\lambda}-1}{\hat{w}} - \frac{2\lambda-1}{\hat{\overline{w}}})$$

$$+\frac{1-\rho}{\theta}\lambda\overline{\lambda}(\overline{\phi}_{t+1}-\phi_{t+1})) + (1-\eta_t)(\delta\hat{R}(\frac{1}{\hat{w}}-\frac{1}{\hat{\overline{w}}}) + \frac{1-\rho}{\theta}(\overline{\varphi}_{t+1}-\varphi_{t+1}));$$

$$> \beta\theta(\eta_t \frac{\delta}{\lambda+\overline{\lambda}-1}(\frac{2\overline{\lambda}(1-\overline{\lambda})\hat{\overline{w}}}{(\delta-\overline{\phi}_{t+1})\hat{w}} - \frac{2\lambda(1-\lambda)\hat{w}}{(\delta-\phi_{t+1})\hat{\overline{w}}} + \frac{\hat{\overline{w}}-\hat{w}}{\hat{\overline{w}}}(\overline{\lambda}-\lambda)$$

$$+\frac{1-\rho}{\theta}\lambda\overline{\lambda}(\overline{\phi}_{t+1}-\phi_{t+1})) + (1-\eta_t)(\delta\hat{R}(\frac{1}{\hat{w}}-\frac{1}{\hat{\overline{w}}}) + \frac{1-\rho}{\theta}(\overline{\varphi}_{t+1}-\varphi_{t+1}));$$

$$> \beta\theta(\eta_t \frac{\delta}{\lambda+\overline{\lambda}-1}(\frac{2}{\delta-\phi_{t+1}}(\frac{\overline{\lambda}(1-\overline{\lambda})\hat{\overline{w}}}{\hat{w}} - \frac{\lambda(1-\lambda)\hat{w}}{\hat{\overline{w}}}) + \frac{\hat{\overline{w}}-\hat{w}}{\hat{\overline{w}}}(\overline{\lambda}-\lambda))$$

$$+(1-\eta_t)\delta\hat{R}(\frac{1}{\hat{w}}-\frac{1}{\hat{\overline{w}}}),$$ since $\overline{\phi}_{t+1} > \phi_{t+1}$ and $\overline{\varphi}_{t+1} > \varphi_{t+1}$;

$$> \beta\theta\eta_t \frac{\delta}{\lambda+\overline{\lambda}-1}\frac{2}{\delta-\phi_{t+1}}(\overline{\lambda}(1-\overline{\lambda})-\lambda(1-\lambda)),$$ since increasing in $\frac{\overline{w}_t}{w_t}$;

>0, since $\lambda > \overline{\lambda}$, $\lambda > \frac{1}{2}$ and $\overline{\lambda} > \frac{1}{2}$.

Similarly, $\overline{\phi}_t > \phi_t$ if $\overline{\varphi}_{t+1} > \varphi_{t+1}$ and $\overline{\phi}_{t+1} > \phi_{t+1}$.

b. Proof that $v_{t+1}^U > v_{t+1}^M$ and $\overline{v}_{t+1}^M > \overline{v}_{t+1}^U$, $\forall t$

i. Proof that $v_T^U > v_T^M$ and $\overline{v}_T^M > \overline{v}_T^U$

$$\overline{v}_T^M - \overline{v}_T^U = \delta\frac{\hat{\overline{R}}}{\hat{\overline{w}}} - \frac{\lambda\overline{\lambda}\delta}{\lambda+\overline{\lambda}-1}(\frac{1}{\overline{\lambda}\hat{\overline{w}}}(\frac{1-\lambda}{\delta}\hat{w} + \frac{2\lambda-1}{\lambda}\hat{\overline{R}}) - \frac{1}{\delta}\frac{(1-\overline{\lambda})\hat{\overline{w}}}{\lambda\hat{w}}),$$ from Equations 2.42 and 2.43;

$$= \frac{1}{\lambda+\overline{\lambda}-1}(\overline{\lambda}(1-\overline{\lambda})\frac{\hat{\overline{w}}}{\hat{w}} - \lambda(1-\lambda)\frac{\hat{w}}{\hat{\overline{w}}} + (\overline{\lambda}-\lambda)\frac{\hat{\overline{R}}\delta}{\hat{\overline{w}}});$$

$$> \frac{1}{\lambda+\overline{\lambda}-1}(\overline{\lambda}(1-\overline{\lambda})\frac{\hat{\overline{w}}}{\hat{w}} - \lambda(1-\lambda)\frac{\hat{w}}{\hat{\overline{w}}} + (\overline{\lambda}-\lambda)\delta\frac{\hat{\overline{w}}-\hat{w}}{2\hat{\overline{w}}}),$$ since $\lambda > \overline{\lambda}$ and $\overline{w}_t > w_t + 2R_t$;

$$> \frac{1}{\lambda+\overline{\lambda}-1}(\overline{\lambda}(1-\overline{\lambda})-\lambda(1-\lambda)),$$ since increasing in $\frac{\overline{w}_t}{w_t}$;

>0, since $\lambda > \overline{\lambda}$, $\lambda > \frac{1}{2}$ and $\overline{\lambda} > \frac{1}{2}$.

$$v_T^U - v_T^M = \overline{v}_T^M - \overline{v}_T^U > 0$$

ii. Proof that $\nu_{t+1}^{U} > \nu_{t+1}^{M}$ and $\bar{\nu}_{t+1}^{M} > \bar{\nu}_{t+1}^{U}$ imply that $\nu_{t}^{U} > \nu_{t}^{M}$ and $\bar{\nu}_{t}^{M} > \bar{\nu}_{t}^{U}$

$$\bar{\nu}_{t+1}^{M} - \bar{\nu}_{t+1}^{U} = \frac{\delta}{\lambda + \bar{\lambda} - 1}\left(\frac{\bar{\lambda}(1-\bar{\lambda})}{\delta - \bar{\phi}_{t+1}}\frac{\hat{\bar{w}}}{\hat{w}} - \frac{\lambda(1-\lambda)}{\delta - \phi_{t+1}}\frac{\hat{w}}{\hat{\bar{w}}} + (\bar{\lambda} - \lambda)\frac{\hat{R}}{\hat{\bar{w}}}\right)$$

$$+ \frac{\beta(1-\rho)}{\theta}(1 - \gamma_{t+1} - \eta_{t+1})(\bar{\nu}_{t+2}^{M} - \bar{\nu}_{t+2}^{U}) \text{, from Equations 2.42 and 2.43;}$$

$$> \frac{\delta}{\lambda + \bar{\lambda} - 1}\left(\frac{\bar{\lambda}(1-\bar{\lambda})}{\delta - \bar{\phi}_{t+1}}\frac{\hat{\bar{w}}}{\hat{w}} - \frac{\lambda(1-\lambda)}{\delta - \phi_{t+1}}\frac{\hat{w}}{\hat{\bar{w}}} + \frac{\bar{\lambda} - \lambda}{2}\frac{\hat{\bar{w}} - \hat{w}}{\hat{\bar{w}}}\right)$$

$$+ \frac{\beta(1-\rho)}{\theta}(1 - \gamma_{t+1} - \eta_{t+1})(\bar{\nu}_{t+2}^{M} - \bar{\nu}_{t+2}^{U});$$

$$> \frac{\delta}{\lambda + \bar{\lambda} - 1}\left(\frac{1}{\delta - \phi_{t+1}}\left(\bar{\lambda}(1-\bar{\lambda})\frac{\hat{\bar{w}}}{\hat{w}} - \lambda(1-\lambda)\frac{\hat{w}}{\hat{\bar{w}}}\right) + \frac{\bar{\lambda} - \lambda}{2}\frac{\hat{\bar{w}} - \hat{w}}{\hat{\bar{w}}}\right)$$

$$+ \frac{\beta(1-\rho)}{\theta}(1 - \gamma_{t+1} - \eta_{t+1})(\bar{\nu}_{t+2}^{M} - \bar{\nu}_{t+2}^{U}) \text{, since } \bar{\phi}_t > \phi_t;$$

$$> \frac{\delta}{\lambda + \bar{\lambda} - 1}\frac{1}{\delta - \phi_{t+1}}(\bar{\lambda}(1-\bar{\lambda}) - \lambda(1-\lambda))$$

$$+ \frac{\beta(1-\rho)}{\theta}(1 - \gamma_{t+1} - \eta_{t+1})(\bar{\nu}_{t+2}^{M} - \bar{\nu}_{t+2}^{U}) \text{, since increasing in } \frac{\bar{w}_t}{w_t};$$

$$> 0 \text{, since } \lambda > \bar{\lambda} \text{, } \lambda > \frac{1}{2} \text{ and } \bar{\lambda} > \frac{1}{2} \text{ and } \bar{\nu}_{t+2}^{M} > \bar{\nu}_{t+2}^{U}.$$

$$\nu_{t+1}^{U} - \nu_{t+1}^{M} = \frac{\delta}{\lambda + \bar{\lambda} - 1}\left(\frac{\bar{\lambda}(1-\bar{\lambda})}{\delta - \bar{\phi}_{t+1}}\frac{\hat{\bar{w}}}{\hat{w}} - \frac{\lambda(1-\lambda)}{\delta - \phi_{t+1}}\frac{\hat{w}}{\hat{\bar{w}}} + (\bar{\lambda} - \lambda)\frac{\hat{R}}{\hat{\bar{w}}}\right)$$

$$+ \frac{\beta(1-\rho)}{\theta}(1 - \gamma_{t+1} - \eta_{t+1})(\nu_{t+2}^{U} - \nu_{t+2}^{M});$$

$$> 0 \text{, given the previous result.}$$

APPENDIX 2

Table 2.A1

Coefficients from Cox proportional hazard model estimates for the probability of divorce

Variable	(i) Females – first divorce	(ii) Females – subsequent divorce	(iii) Males – first divorce	(iv) Males – subsequent divorce
Age at marriage	-0.107***	-0.204***	-0.139***	-0.369***
	(0.018)	(0.059)	(0.022)	(0.126)
Age difference	0.005	-0.049	0.014	0.126**
	(0.015)	(0.034)	(0.020)	(0.068)
Black non-Hispanic	0.515***	0.788	0.509***	2.787***
	(0.156)	(0.623)	(0.194)	(0.874)
Hispanic	0.120	-0.289	-0.504**	0.050
	(0.189)	(0.659)	(0.217)	(0.917)
Catholic	-0.450**	-0.314	0.065	-1.044
	(0.180)	(0.674)	(0.200)	(0.890)
Baptist	-0.063	-0.366	0.054	-1.537**
	(0.158)	(0.568)	(0.188)	(0.839)
Other protestant	-0.197	-0.109	-0.081	-1.069
	(0.179)	(0.604)	(0.210)	(0.849)
Frequency of religious attendance	-0.217*	-0.181	-0.320**	-2.261**
	(0.118)	(0.458)	(0.156)	(0.974)
Poor health	0.132	0.465	0.428	–
	(0.250)	(0.638)	(0.342)	
Highest grade completed	-0.006	-0.014	-0.105***	-0.005
	(0.031)	(0.116)	(0.038)	(0.224)
AFQT score	-0.010***	-0.003	-0.003	-0.003
	(0.003)	(0.011)	(0.003)	(0.016)
Spouse income (in 1000s)	-0.002	0.009**	-0.008	-0.043
	(0.002)	(0.004)	(0.006)	(0.030)
Non-wage income (in 1000s)	0.000	-0.696	0.010	0.000
	(0.001)	(0.635)	(0.007)	(0.071)
Parents divorced	0.174	-0.199	0.475***	-0.233
	(0.136)	(0.459)	(0.158)	(0.732)
Urban	0.155	-0.463	0.434**	-0.715
	(0.137)	(0.460)	(0.172)	(0.822)
Child present	-0.044	-0.919	-0.557***	-2.045
	(0.159)	(0.730)	(0.173)	(0.973)
Child before marriage	0.419***	0.882	0.552***	0.989**
	(0.138)	(0.673)	(0.155)	(0.754)
Number of observations	17,993	2,112	16,037	1,267
Number of individuals	2,125	453	2,033	314

Note: Standard errors are presented in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Poor health was not included in the fourth specification as none of the men who were within

Table 2.A2
Coefficients from Cox proportional hazard model estimates for the probability of marriage and remarriage

Variable	(i) Females – first marriage	(ii) Females – subsequent marriage	(iii) Males – first marriage	(iv) Males – subsequent marriage
Black non-Hispanic	-0.630***	-1.247***	-0.654***	-0.582**
	(0.068)	(0.247)	(0.068)	(0.285)
Hispanic	-0.097	0.029	-0.039	0.294
	(0.065)	(0.200)	(0.066)	(0.292)
Catholic	-0.039	-0.527**	-0.237***	-0.132
	(0.064)	(0.209)	(0.063)	(0.289)
Baptist	0.047	-0.017	-0.027	0.129
	(0.068)	(0.212)	(0.069)	(0.284)
Other protestant	-0.053	0.047	-0.143**	0.188
	(0.067)	(0.193)	(0.067)	(0.308)
Frequency of religious attendance	0.126***	0.187	0.137***	0.264
	(0.044)	(0.209)	(0.048)	(0.204)
Poor health	-0.034	-0.675*	-0.078	0.027
	(0.108)	(0.387)	(0.123)	(0.424)
Highest grade completed	-0.071***	0.046	-0.048***	0.140**
	(0.011)	(0.040)	(0.011)	(0.055)
AFQT score	0.001	-0.001	0.003**	-0.002
	(0.001)	(0.004)	(0.001)	(0.005)
Non-wage income (in 1000s)	0.012**	-0.023	0.000	-0.027
	(0.006)	(0.027)	(0.001)	(0.037)
Parents divorced	-0.089	-0.091	-0.079	-0.287
	(0.055)	(0.169)	(0.060)	(0.275)
Urban	-0.148***	-0.091	-0.180***	-0.331
	(0.051)	(0.169)	(0.052)	(0.228)
Child present	-0.266***	-0.596***	0.186**	0.095
	(0.065)	(0.146)	(0.104)	(0.228)
Expected marriage age	-0.289***	-0.264***	-0.200***	-0.129
	(0.030)	(0.062)	(0.029)	(0.084)
Number of observations	28,345	5,885	33,323	4,430
Number of individuals	3,393	1,177	3,565	991

Note: Standard errors are presented in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

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3. The dynamics of productivity spillovers in Major League Baseball

"A horse never runs so fast as when he has other horses to catch up and outpace."
OVID

One labor market where productivity spillovers clearly exist between co-workers is that for professional team sports. Output is directly related to team performance, which is likely to be a complex function of the output of individual players. With salary data for individual players and information on the teams they play for over their careers, it is possible to assess the extent to which the performance of a player's team-mates affects his/her income, after controlling for the player's own performance. The major benefit of studying the labor market for sportsmen is that detailed measures of individual productivity are easily obtained, rather than simply the crude proxies of education and experience that are typically used in studies of the general labor market. This allows one to accurately measure the contributions to team output made by individual players.

Although baseball is a team sport, it has a large set of well-defined individual performance statistics, making it an ideal setting in which to untangle the contributions of individual and team productivity to a player's salary. Team performance is unlikely to have much effect on salary after controlling for individual performance measures for precisely this reason; general managers are able to observe a person's "numbers" in each season. However, this does not imply that team-mates have no effect on a player's earnings since they may influence his individual statistics, which are certain to be related to pay.

A player's performance may be influenced by the performance of his team-mates in two ways. Firstly, his individual statistics may be "inflated" by the presence of highly productive players on his team in the same season. For example, a player's batting average is likely to improve if he hits before a slugger in the order. This type of effect is a true spillover, in the sense that it does not increase the person's true ability and is purely transitory – if the slugger were to leave the team, his team-mates would suffer a fall in their averages. In contrast, if players learn from their team-mates, they will play better in future seasons, regardless of where they are and who they play alongside. These two effects can be distinguished empirically by looking at whether a player's performance measures are influenced by his team-mates' performance in the same season or in previous seasons. Evidence of the former indicates the existence of spillovers; evidence of the latter indicates that learning takes place. Few previous studies have focused on whether co-worker spillovers are lasting or not since labor economists rarely have accurate, time-varying measures of individual productivity.

In this paper, the determinants of the performance and incomes of Major League Baseball players are examined. Firstly, regressions for a number of individual performance statistics are used to explore whether there is evidence of either spillovers or learning by either pitchers or position players. Secondly, salary is regressed on individual performance measures, thus providing an indication of how much a given change in team performance will influence individual salaries in the future. Longitudinal data are used, allowing unobserved player-specific heterogeneity and team-specific heterogeneity may also be controlled for. Few previous studies have analyzed longitudinal baseball data and none of these have looked at productivity spillovers or have allowed for team effects in a salary regression.

Evidence of both spillovers and learning is uncovered. For example, among pitchers earned run average (ERA) is positively related to both contemporaneous team-mate ERA and lagged team-mate ERA. A batter's average will be higher if his team-mates' averages are high in the previous season only. Salary is found to be closely tied to individual performance and hence, indirectly, to team performance.

Even though the baseball labor market is a highly atypical one, the results of this paper have wider implications within labor economics, since they provide a rare insight into the ways in which people's output (rather than income) is influenced by their colleagues. Some of this is due to pure spillovers and is fleeting, however there is also evidence that people make lasting productivity gains when they have high-performing co-workers. These results suggest that the contributions of co-worker ability may be easily overlooked in other settings, since even if co-worker ability is found to have little effect on earnings after controlling for individual human capital, it may operate indirectly from year to year through individual ability.

1. Previous work

Rosen and Sanderson (2000) reviewed the main issues in the analysis of labor markets for professional sportsmen. They noted that the marginal revenue product of a player is the extra price that a spectator is willing to pay multiplied by the number of people who are attracted in person or on television. They suggested that the audience-quality gradient is very steep while the price-quality gradient is very flat. This means that top players earn extremely high salaries because they attract the largest audience. Rosen (1981) formalized this argument with a production function similar to those used by Lucas (1978) and Rosen (1982) in the study of managerial pay within firms.

One of the few papers that have directly examined the effect of team performance on individual players' salaries is Idson and Kahane (2000), who focused on the National Hockey League. They used the following specification for salaries:

$$\ln y_i = \beta_0 + \sum_{j=1}^{J} \beta_{1j} x_{ij} + \sum_{k=1}^{K} \beta_{2k} \bar{x}_{ik} + \sum_{j=1}^{J} \sum_{k=1}^{K} \beta_{3jk} x'_{ij} \bar{x}_{ik} + \sum_{l=1}^{L} \beta_4 z_{il} + \varepsilon_i , \qquad (3.1)$$

where x_i is a set of individual performance measures, $\bar{x}_i$ is the corresponding set of team performance measures and z_i represents additional regressors. The marginal effects of individual and team performance are then given by:

$$\frac{\partial \ln y_i}{\partial x_i} = \beta_1 + \beta_2 \bar{x}_i ; \qquad (3.2)$$

$$\frac{\partial \ln y_i}{\partial \bar{x}_i} = \beta_1 + \beta_2 x_i . \qquad (3.3)$$

The inclusion of an interaction term in Equation 3.1 therefore means that team performance may not only have a direct effect on pay (β_2) but also an indirect effect, by altering the rate at which individual productive characteristics are valued (β_3). The sign on β_3 determines whether particular inputs are complements ($\beta_3 > 0$) or substitutes ($\beta_3 < 0$) in production.

Idson and Kahane focused on a relatively small cross-section constructed from two seasons of data. Along with average player attributes for each team, they included performance measures for the team's coach in $\bar{x}_i$. Overall, they found that the team measures have both a direct and indirect effect on pay. Players tend to be complements in production, although there is no uniform pattern across the productive attributes used. Coaching quality is found to have a significant effect, although the results suffer from multicollinearity between the chosen variables.

Among previous papers that have addressed aspects of earnings functions in Major League Baseball, Kahn (1993) examined the impact of the introduction of free agency and salary arbitration in 1976 on salary and contract duration.[1] He used a four-year longitudinal dataset covering almost all major league players, with earlier information for those on long-term contracts. Fixed effects regressions were estimated separately

[1] Kahn (2000) presented a discussion of the emergence of free agency in baseball.

for both pitchers and non-pitchers, with the unit of observation being a contract for an individual player. Kahn found that both arbitration and free agency eligibility increased salary and the latter also increased contract duration.

In another paper, Kahn (1993a) investigated the effect of managerial quality on team and individual performance. The measures of managerial quality and performance used were predicted pay based on regressions that controlled for productivity characteristics, while team performance was a team's winning percentage.[2] Kahn found that better managers produce better team performances, after controlling for player inputs. In addition, higher-quality managers tend to yield improvements in player performance, relative to previous levels.

Blass (1992) examined whether major league baseball players are paid in a manner that is consistent with the human capital model, which predicts that incomes rise with experience only because of productivity increases. To obtain a measure of productivity for each player, he first estimated winning percentage as a function of runs scored and conceded and then estimated team revenue as a function of wins. Individual productivity was calculated using the estimated coefficients from these equations. Blass then included this term in an earnings function, along with experience terms.[3] The fact that experience is found to have a significant effect on pay independent from productivity is interpreted as evidence that the major league baseball labor market violates the human capital model. Blass instead suggested that an implicit contract model may apply, since older players are overpaid, relative to younger players.

Using two seasons of data, MacDonald and Reynolds (1994) took a similar approach to Blass and found that experienced players paid in accordance with their

[2] A drawback of Kahn's analysis was that, although he used a panel to examine the effects of managerial quality, his salary regressions were based only on a single year of data.

[3] Blass used both a cross-sectional earnings equation for all players and an eight-year panel for more experienced players only.

marginal revenue products, while younger players are paid less than their marginal products. They also provided the first empirical support for Rosen's (1981) model, with their results suggesting that returns to talent are convex.

Further evidence was reported by Fields (2001), who found that all Major League Baseball players are paid less than their marginal revenue products, but, as noted by MacDonald and Reynolds, older players receive salaries closer to their marginal products than younger players.[4] Fields followed a similar two-stage method for calculating marginal revenue product as Blass and MacDonald and Reynolds, first regressing team revenue on winning percentage and then regressing winning percentage on team performance measures. This approach requires the assumption that individual performance generates no externalities, so that team performance is the summation of individual performance. Fields then examined the relationship between players' salaries and estimated marginal revenue products in a simple regression. This paper was one of the first to use a panel of individual salary information and used a similar (but shorter) dataset to the one described below. Since his main regressions were at the team level, he was able to include team and year effects, however he failed to fully exploit the panel aspect of the data by including player effects in his individual-level regressions.

2. Data

A detailed longitudinal dataset was assembled from the Baseball Archive (Version 5.1) website. This data source contains annual data for every player over the entire history of the major leagues, however for the purposes of this study, a dataset was

[4] Earlier work by Sommers and Quinton (1982) followed a similar approach and found that the first wave of free agents received salaries similar to their marginal revenue products, whereas other players were underpaid.

created for the period 1950-2003. This contains a wide range of output characteristics for each player, along with salary information for 1985 onwards. It can be considered equivalent to a linked employer-employee dataset, as the data follow players as they move from team to team over the course of their careers. The final dataset is at an annual frequency, with the statistics for players who appear for more than team in a season aggregated appropriately. A player is classified as a pitcher if he pitched in any game during a season, unless he pitched in fewer than 4 games and batted in at least 15 games, in which he is considered a non-pitcher. Details of the 39 teams that are used in the analysis are given in Appendix 1.[5] For the purposes of this analysis, a new team is assumed to be created whenever a team moves cities.

Means for the samples used in the performance regressions in Section 4 are presented in Table 3.1. As will be discussed later, three years of data are lost due to the model specification and estimation technique, so the data here cover the period 1953-2003. Non-pitchers are seen to have slightly longer careers than pitchers on average. They also have a significantly higher chance of being selected for the all-star team.

Although the dataset includes annual salary from 1985, it does not include details about the start and finish dates of players' contracts. In order to construct a contract-level dataset, additional information were obtained for contracts signed since 1998 and these were merged with the primary data.[6] Of the 7,286 player-year observations over the 1998-2003 period, contract details are known for 2,056, that is, in 28% of cases. Using this information, the average real salary over the duration of the contract was computed. The analysis in Section 4 also uses annual salary data for 1985-2003 for

[5] The Boston Braves existed until 1952, however, as noted in the text, the earliest observations that are actually used in the analysis are from 1953.

[6] Data were also collected on a few contracts signed before 1998 but these are excluded from the analysis.

Table 3.1
Means for the performance regression samples

Variable	Pitchers	Non-pitchers
Experience	7.061	7.390
All star appearances	0.081	0.130
Win percentage	0.457	–
Earned run average	4.428	–
Start percentage	0.459	–
Save percentage	0.059	–
Batting average	–	0.252
Extra bases/at bats	–	0.202
Walks/at bats	–	0.103
Stolen bases/game	–	0.049
Gold Glove	–	0.049
Catcher	–	0.152
Infield	–	0.311
Team earned run average	3.961	3.926
Team save percentage	0.204	0.219
Team batting average	0.260	0.258
Team extra bases/at-bats	0.213	0.210
Team walks/at-bats	0.098	0.097
Team stolen bases/game	0.622	0.583
Number of observations	9,246	13,876

Notes: Data are at an annual frequency for 1953-2003.

those players who are in their first six years in the major leagues and have therefore not attained free agency status. In both cases, average salary is expressed in constant (2000) dollar values, using the price deflator from the Consumer Price Index.

Means for the contract-level and annual datasets are presented in Table 3.2. Roughly two-thirds of the contracts are for one year and most commence in the last three years of the sample period. In comparison, the annual sample has a much lower average salary, due to the fact that this sample contains observations for earlier years and only includes players with relatively little experience and little bargaining power.

3. Approach

The first stage of the analysis involves analyzing the determinants of various individual productivity measures. The same set of statistics was selected as in Kahn

Table 3.2
Means for the salary regression samples

Variable	Pitchers	Non-pitchers
Contract-level sample:		
Commenced in 1998-2000	0.134	0.157
Commenced in 2001	0.230	0.217
Commenced in 2002	0.240	0.240
Commenced in 2003	0.397	0.386
One year duration	0.661	0.652
Two year duration	0.152	0.109
Three year duration	0.114	0.090
Four year duration	0.052	0.088
Five years or more duration	0.022	0.061
Average contract salary	3,129,500	3,379,948
Number of observations	501	658
Annual sample:		
Average salary	976,610	1,083,565
Number of observations	2178	2699

Notes: Salary is expressed in constant (2000) dollar values.

(1993). For pitchers, these are ERA, winning percentage, the percentage of games in which he started, the percentage of appearances that resulted in a save and a dummy variable for whether he was named on the all-star team that season. For non-pitchers, they are batting average, extra bases obtained through extra base hits per at bat, walks per at bat, stolen bases per game, dummy variables for catchers and non-first base infielders, a dummy variable for whether the player was named on the all-star team and a dummy variable for whether he won a Gold Glove award. Each of these variables is regressed in turn on two lags of the full set of individual performance measures and the contemporaneous value and first lag of a set of team-mate performance measures, along with a quadratic in major league experience:

$$y_{it}^{j} = \mathbf{y}_{i(t-1)}\boldsymbol{\alpha}_1^j + \mathbf{y}_{i(t-2)}\boldsymbol{\alpha}_2^j + \mathbf{Y}_{it}\boldsymbol{\beta}_0^j + \mathbf{Y}_{i(t-1)}\boldsymbol{\beta}_1^j + \mathbf{X}_{it}\boldsymbol{\delta}^j + \theta_i^j + \lambda_t^j + \mu_{s(i,t)}^j + \varepsilon_{it}^j , \quad (3.4)$$

where y_{it}^{j} is the *j*th element of the matrix of individual performance measures for player *i* in year *t*, $\mathbf{y}_{it}$; $\mathbf{Y}_{it}$ is a set of performance measures (both for pitching and batting) calculated across a player's team-mates in a given year; $\mathbf{X}_{it}$ includes experience and experience squared; θ_i^j is a player fixed effect; $\mu_{s(i,t)}^j$ is a team fixed effect; and λ_t^j is a year fixed effect.[7] The team performance measures that are included in **Y** are ERA, batting average, extra bases per at bat and walks per at bat.[8]

The $\boldsymbol{\beta}_0$ coefficients are assumed to capture the effect of contemporaneous teammate spillovers while the $\boldsymbol{\beta}_1$ coefficients will be interpreted as reflecting learning effects that persist from year to year.

Since Equation 3.4 includes two lags of the dependent variable on the right hand side, it cannot be estimated using traditional panel data techniques. Instead, the method of Arellano and Bond (1991) may be employed. In the present context, this involves first-differencing the equation to remove θ and then estimating the differenced equation with instrumental variables, where the lagged dependent variables are instrumented by earlier lags of y.

Salary regressions will also be estimated to assess how closely pay is tied to individual performance. The following specification will be used:

$$\ln w_{ic(t)} = \mathbf{y}_{i(t-1)}\boldsymbol{\gamma}_1 + \bar{\mathbf{y}}_{i(t-2)}\boldsymbol{\gamma}_2 + \mathbf{Z}_{it}\boldsymbol{\delta} + \eta_i + \pi_t + \psi_{s(i,t)} + \varsigma_{it}, \tag{3.5}$$

where $w_{ic(t)}$ is the average real (in 2000 dollars) annual salary received by player i under contract c, which begins in year t, $\bar{\mathbf{y}}$ is a person's average performance over his entire career and $\mathbf{Z}_{it}$ includes experience, experience squared and three dummies for free agency eligibility status. A player is eligible for free agency after six years of major league experience and is generally eligible for salary arbitration after three years of experience.[9] Hence, following Kahn (1993), the free agency dummies identify

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[7] Including two lags of the individual performance measures allows current performance to be a function of recent performance. If they are excluded, standard fixed effects estimation can be used, although the results are very similar to those presented in the next section.

[8] **Y** has an i subscript in Equation 3.4 to indicate that it is calculated exclusive of player i. Team winning percentage, team save percentage and team stolen bases/game are not included as they are arguably endogenous to individual performance.

[9] A player is also eligible for salary arbitration if he meets the so-called "super two" exception, namely that he has two years of experience, played in the major leagues for at least 86 days in the previous season and is among the top 17% of players for cumulative playing time in the major leagues amongst those with exactly two years of experience. This exception is ignored here.

those players who have three or four years of experience and are thus eligible for salary arbitration but not in their last year of eligibility; those who have exactly five years of experience and, as such, are in their last year of eligibility for salary arbitration; and those who have at least six years of experience and are therefore free agents. The contract length dummies identify those contracts that are for two years, three years, four years and five years or more. For pitchers, **y** also includes, in addition to the variables described earlier, the interaction of start percentage with winning percentage, ERA and save percentage.

4. Results

a. Performance equations

The results of estimation of Equation 3.4 for pitchers are presented in Table 3.3. Although not reported, the coefficients on the lags of the individual performance measures indicate that performance exhibits hysteresis. The year effects are jointly significant for ERA, winning percentage and start percentage, indicating that there have been no major trends in the other pitching statistics used.[10]

The results in Table 3.3 suggest that both productivity spillovers and learning occur among pitchers. Players benefit if their pitching colleagues play well during a season. A 1 run decrease in a team-mate ERA results in a 0.324 run reduction in a pitcher's ERA during the same season. Not surprisingly, a player's winning percentage is positively related to the team's offensive ability, including batting average and extra bases and walks per at bat, and other pitchers' ERAs. In addition, a

[10] A requirement of Arellano-Bond estimation is that the differenced error terms not exhibit second order autocorrelation. All the models in Tables 3.3 and 3.4 satisfy this requirement except the start percentage regression for pitchers and batting average regression for non-pitchers.

Table 3.3
Performance regressions for pitchers

Variable	Earned run average	Winning percentage	Start percentage	Save percentage	All-star
Current value:					
Team earned run	0.324***	-0.029***	0.042***	0.003	-0.012
average	(0.081)	(0.008)	(0.007)	(0.003)	(0.009)
Team batting	-2.484	1.895***	0.191	0.037	-0.057
average	(4.881)	(0.352)	(0.343)	(0.114)	(0.430)
Team extra	0.402	0.647***	-0.446***	0.009	-0.105
bases/at-bats	(2.731)	(0.156)	(0.168)	(0.057)	(0.184)
Team walks/at-	-1.424	1.280***	-0.314	-0.074	0.417
bats	(3.545)	(0.285)	(0.270)	(0.109)	(0.322)
Lagged value:					
Team earned run	0.312***	-0.021***	0.006	0.000	-0.000
average	(0.119)	(0.007)	(0.007)	(0.003)	(0.008)
Team batting	-9.220	0.503	1.151***	-0.016	0.528
average	(6.718)	(0.346)	(0.335)	(0.119)	(0.400)
Team extra	1.168	0.308*	0.172	-0.005	-0.029
bases/at-bats	(2.029)	(0.163)	(0.154)	(0.052)	(0.167)
Team walks/at-	-10.195**	0.507*	0.590**	-0.219**	-0.071
bats	(4.627)	(0.284)	(0.281)	(0.106)	(0.307)
Pseudo R-squared	0.024	0.040	0.009	0.041	0.056
Number of observations	9,246	9,246	9,246	9,246	9,246

Notes: All models also include two lags of the pitcher performance measures, experience, experience squared and a full set of player, team and year dummies.
Arellano-Bond estimation is used, with the third and fourth lags of the dependent variable used to instrument the lags of the dependent variable.
Standard errors are presented in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

player is likely to start more games if his fellow pitchers record high ERAs and he plays for a weak-hitting team.

In addition, the lagged values of some team performance measures have significant coefficients, suggesting that pitchers learn from their team-mates. A 1 run reduction in a player's team-mates' collective ERA will reduce his ERA in the following season by 0.312. A pitcher is also likely to win more games if his colleagues had low ERAs and will start more games if his team's batting average was high.

Table 3.4 presents the results of the performance regressions for non-pitchers. The year effects are jointly significant in all cases except the all-star and Gold Glove

Table 3.4
Performance regressions for non-pitchers

Variable	Batting average	Extra bases/ at-bats	Walks/ at-bats	Stolen bases/game	All-star	Gold Glove
Current value:						
Team earned run average	-0.001 (0.002)	0.003 (0.002)	-0.003* (0.002)	0.001 (0.001)	-0.000 (0.008)	-0.009* (0.005)
Team batting average	0.050 (0.061)	0.005 (0.090)	-0.056 (0.054)	-0.105** (0.053)	0.358 (0.365)	0.597*** (0.224)
Team extra bases/at-bats	-0.018 (0.031)	0.074 (0.046)	0.022 (0.034)	-0.071*** (0.027)	-0.050 (0.171)	-0.063 (0.094)
Team walks/at-bats	0.085* (0.051)	0.120 (0.080)	0.090* (0.051)	0.104** (0.046)	0.085 (0.284)	0.326* (0.183)
Lagged value:						
Team earned run average	0.001 (0.001)	-0.002 (0.002)	-0.000 (0.001)	-0.001 (0.001)	-0.007 (0.008)	0.003 (0.005)
Team batting average	0.137** (0.058)	0.161* (0.096)	-0.003 (0.055)	0.010 (0.053)	0.126 (0.356)	0.308 (0.216)
Team extra bases/at-bats	-0.021 (0.030)	-0.017 (0.047)	-0.026 (0.028)	0.009 (0.023)	-0.114 (0.165)	-0.001 (0.100)
Team walks/at-bats	0.046 (0.047)	-0.015 (0.080)	0.018 (0.060)	-0.031 (0.043)	0.740*** (0.277)	0.026 (0.159)
Pseudo R-squared	0.045	0.015	0.010	0.088	0.141	0.122
Number of observations	13,876	13,876	13,876	13,876	13,876	13,876

Notes: All models also include two lags of the non-pitcher performance measures, experience, experience squared and a full set of player, team and year dummies.
Arellano-Bond estimation is used, with the third and fourth lags of the dependent variable used to instrument the lags of the dependent variable.
Standard errors are presented in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

awards. Once again, there appears to be evidence of both productivity spillovers and learning. A player's batting average is positively related to how often his team-mates walk, suggesting that players benefit from having patient players alongside them in the line-up. An individual's stolen bases per game are negatively related to the team's batting average and frequency of extra base hits, consistent with the notion that players steal more bases to compensate for a lack of power hitting in the line-up. Finally, a player's chances of winning a Gold Glove are enhanced if his team's collective ERA is low and their team-mates score a lot of hits and walks.

Learning appears to take place among batters with batting average and extra bases per at-bat being positively related to team-mates' batting average in the previous year. A 0.1 increase in team batting average will increase a player's average by 0.014 in the next season.

b. Salary equations

The results of estimating Equation 3.5 for pitchers using the contract-level dataset are reported in Table 3.5. The first column includes only individual performance measures, while the second column adds team measures. In all cases, free agents and those eligible for arbitration only are found to earn more than those eligible for neither arbitration nor free agency. Salary is negatively related to a player's ERA two seasons before the contract begins. The corresponding results for non-pitchers are presented in Table 3.6. Batting average and the number of extra bases per at bat are found to be strongly positively related to average salary. Although not reported in Tables 3.5 and 3.6, average contract salary is found to be concave in major league experience for both pitchers and batters and longer contracts are associated with higher salaries. The team effects are not jointly significant in any case, while the player effects are jointly significant for the non-pitcher regressions only.

When team performance characteristics are added to the estimation equation in the second columns of Tables 3.5 and 3.6, a number of the coefficients are significant. Team-mate performance in the previous period influences the pay of pitchers, while non-pitchers are affected most by team-mate performance over their entire careers. While these results imply that team-mate ability has a direct effect on salary, Tables 3.3 and 3.4 have established that it also operates indirectly through its influence on individual performance. The overall impact of the team performance measures may therefore be larger than the estimates in Tables 3.5 and 3.6.

The results in Tables 3.5 and 3.6 are largely consistent with the findings of Kahn

Table 3.5
Salary regressions for pitchers using contract-level sample

Variable	(i)		(ii)	
	Lag	Career	Lag	Career
Arbitration eligible (but not in last year)	0.558		0.545	
	(0.365)		(0.363)	
Last year before free agency	1.127**		1.069**	
	(0.462)		(0.458)	
Free agent	1.157*		0.999*	
	(0.590)		(0.588)	
Win percentage	0.196	-8.080	-1.345	-10.580*
	(2.446)	(5.274)	(2.440)	(5.341)
Earned run average	-0.069	-0.242	-0.097	-0.094
	(0.097)	(0.228)	(0.100)	(0.240)
Start percentage	0.303	-2.577	-0.115	-2.326
	(1.045)	(1.974)	(1.067)	(1.943)
Save percentage	0.821	1.528	1.008	1.559
	(0.826)	(4.111)	(0.798)	(4.009)
Start percentage × win percentage	1.460	9.728*	3.347	12.291**
	(2.760)	(5.256)	(2.782)	(5.350)
Start percentage × earned run average	-0.037	0.199	-0.026	-0.061
	(0.159)	(0.289)	(0.161)	(0.290)
Start percentage × save percentage	4.272	3.307	10.927	9.209
	(13.552)	(13.685)	(13.252)	(13.880)
All-star appearances	0.206	-0.392	0.210	-1.957
	(0.311)	(1.733)	(0.312)	(1.843)
Team earned run average			0.379*	-1.244
			(0.216)	(0.832)
Team batting average			3.799	-4.208
			(9.032)	(34.280)
Team extra bases/at-bats			-34.091**	1.942
			(13.023)	(53.261)
Team walks/at-bats			14.379*	-3.985
			(7.373)	(34.723)
corr(η,ψ)	-0.533***		-0.457***	
R-squared	0.948		0.957	
Number of observations	501		501	

Notes: All models also include a full set of player, team and year dummies.
Standard errors are presented in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

(1993), although they are generally weaker, which is likely a result of the smaller sample size here. This is due to the limited amount of contract information that could be collected. An alternative approach is to use annual salary data for the entire period they are available, 1985-2003, but to restrict the sample to those people who have not attained free agency, *i.e.* those with less than six years of major league experience.

Table 3.6
Salary regressions for non-pitchers using contract-level sample

Variable	(i)		(ii)	
	Lag	Career	Lag	Career
Arbitration eligible (but not in last year)	-0.062 (0.255)		0.053 (0.257)	
Last year before free agency	0.096 (0.321)		0.191 (0.323)	
Free agent	0.097 (0.394)		0.205 (0.398)	
Batting average	3.471*	2.526	3.649**	1.613
	(1.793)	(2.174)	(1.817)	(2.213)
Extra bases/at-bats	3.812***	-1.654	3.508***	-1.149
	(0.983)	(1.937)	(1.013)	(1.964)
Walks/at-bats	-0.551	6.288*	-0.964	5.982
	(1.606)	(3.564)	(1.670)	(3.660)
Stolen bases/game	2.347**	2.428	2.460**	1.873
	(1.154)	(2.640)	(1.153)	(2.749)
All-star appearances	0.257**	1.740***	0.257*	1.807***
	(0.138)	(0.654)	(0.137)	(0.672)
Gold Glove	-0.260	-0.508	0.257*	-0.697
	(0.194)	(1.120)	(0.136)	(1.117)
Catcher	-0.410 (0.267)		-0.445* (0.265)	
Infield	0.265 (0.177)		0.194 (0.176)	
Team earned run average			0.031	0.723*
			(0.102)	(0.371)
Team batting average			3.077	43.191**
			(4.823)	(20.397)
Team extra bases/at-bats			7.667	-49.003
			(8.317)	(31.276)
Team walks/at-bats			-3.825	-30.098*
			(4.352)	(16.478)
corr(η,ψ)	-0.299***		-0.246***	
R-squared	0.948		0.952	
Number of observations	659		659	

Notes: All models also include a full set of player, team and year dummies.
Standard errors are presented in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Figure 3.1 shows that the contract length-experience profile has a U shape. Although a sizeable fraction of non-free agents are on multiple-year contracts, the vast majority are in the first year of a contract. To this extent, it seems reasonable to think that these players' annual salaries will be influenced by their performances in the previous two years.

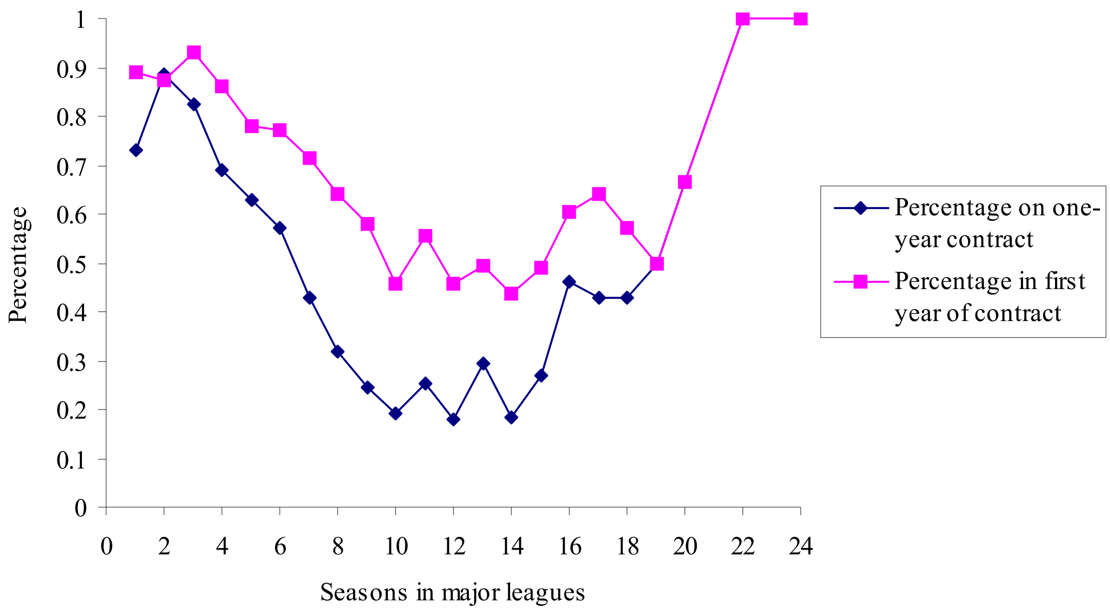

Figure 3.1
Experience and contract length

The first column of Table 3.7 presents the results of salary regressions for pitchers using this sample and excluding team variables. As noted in Table 3.5, salary is negative related to a player's ERA, however save percentage and all-star appearances in the previous two years are also found to have significant effects on salary in any given season. Similarly, the first column of Table 3.8 supports the findings of Table 3.6 and finds a strong positive relationship between salary and both batting average and extra base average. In addition, a player's salary will be higher if in the previous two seasons he stole a lot of bases, was an all-star or won a Gold Glove.

Tables 3.7 and 3.8 also report the results of salary regressions for those players who have attained free agency, *i.e.* those players with at least seven years of experience. Since many of these players may be on multiple-year contracts, annual salary may be determined years in advance and may not reflect a player's recent performance level. On the other hand, free agents are more likely to be paid according

Table 3.8
Salary regressions for non-pitchers using annual data

Variable	Non-free agents		Free agents	
	Lag	Career	Lag	Career
Batting average	0.970***	0.023	3.963***	22.136***
	(0.263)	(0.218)	(0.357)	(1.998)
Extra bases/at-bats	0.553***	0.659***	0.288	3.598***
	(0.157)	(0.159)	(0.187)	(0.925)
Walks/at-bats	0.414	0.066	0.166	3.834**
	(0.286)	(0.250)	(0.310)	(1.566)
Stolen bases/game	0.989***	0.050	0.883***	1.065
	(0.240)	(0.320)	(0.228)	(0.820)
All-star appearances	0.352***	0.893***	0.070**	0.954***
	(0.053)	(0.164)	(0.034)	(0.207)
Gold Glove	0.316***	0.566**	-0.059	0.174
	(0.080)	(0.251)	(0.053)	(0.266)
corr(η,ψ)	-0.170***		0.009	
R-squared	0.888		0.862	
Number of observations	2,700		3,259	

Notes: All models also include a quadratic in experience and a full set of year dummies, player dummies and team dummies.
Standard errors are presented in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Notes: All models also include a quadratic in experience and a full set of year dummies, player dummies and team dummies.
Standard errors are presented in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

to their market value. Free agent pitchers, in particular, are found to have salaries that are closely related to their recent performance. Over the course of a pitcher's career, however, the most important salary determinant is ERA. Non-pitchers, in contrast, appear to be remunerated largely according to their career output, although previous season batting average and stolen bases are also positively related to salary, as is being named on the all-star team.

Tables 3.5-3.8 also report the correlations between the estimated player and team effects. In all specifications except the second column of Table 3.8, this is found to be negative and significant, suggesting that there is negative assortative matching in the baseball labor market. This is a surprising finding, albeit one that is consistent with many of the papers estimating wage equations using linked employer-employee

Table 3.9
Effect of team performance on log salary

Variable	Pitchers		Non-pitchers	
	Lag	Career	Lag	Career
Team earned run average	0.030***	8.587***	0.003	-0.003
	(0.008)	(0.099)	(0.005)	(0.005)
Team batting average	0.719	-808.941***	0.028	0.810*
	(0.520)	(11.815)	(0.213)	(0.430)
Team extra bases/at-bats	-0.366**	-63.681***	-0.100	-0.370
	(0.146)	(3.760)	(0.122)	(0.261)
Team walks/at-bats	-0.258	-155.451***	0.451***	1.138***
	(0.337)	(9.039)	(0.127)	(0.383)

Notes: Bootstrapped standard errors are presented in parentheses, where 30 replications are used. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

data.[11] Figures 3.A1 and 3.A2 plot the estimated team effects against the average player effect for each team, using the results from Tables 3.7 and 3.8, respectively. For pitchers, the Arizona Diamondbacks and Tampa Bay Devil Rays, two recently-formed teams, have very high player effects, while also having relatively small team effects. This pattern is not noticeable among non-pitchers, although there is still a high degree of heterogeneity between teams.

Table 3.9 assesses the overall impact that team performance has on salary, using the annual salary data but including both free agents and non-free agents in the regressions. Bootstrapped standard errors are presented for each coefficient. The first and third columns report the effect that team variables have on an individual's salary in the following year. These values are the elements of the vector $\boldsymbol{\beta}_0\boldsymbol{\gamma}_1$, where $\boldsymbol{\beta}_0 = [\boldsymbol{\beta}_0^j]$. The second and fourth columns of the table indicate what effect a given increase in team-mate performance has over a player's entire career. These are calculated by first simulating the effect of a one unit increase in each team

[11] Barth and Dale-Olsen (2003) noted that if it is impossible for anyone to distinguish between the component of productivity that is due to the firm (or team) and the component that is due to the worker (or player), then it is only the sum of these terms that matters to all agents. In this case, the estimation method could lead to a negative observed correlation between firm and worker effects, even if the two factors are complements in production.

productivity measure in every year a player appears in the dataset, starting with his debut season, taking into account the indirect effects team performance has on individual performance from one year to the next. The reported coefficient is the average value of this variable over all players and years. It is seen that team-mate performance has some significant effects on salary in the following season. The results for pitchers are strongest and suggest that they are paid better if they play for teams with weak pitching and hitting. In contrast, non-pitchers are paid better if they play alongside hitters with high averages and who walk often.

5. Conclusion

This paper has exploited a rich source of performance and salary data for major league baseball players to examine the ways in which team-mate ability influences a player's performance each year. Any impacts contemporaneous team performance may have on individual performance are termed spillovers, while the effect of team performance in previous seasons is considered indicative of learning amongst players. Evidence of both effects is found in the data. Pitchers play better if the pitchers on the same team played well in the same season or the previous season; batters achieve more and heavier hits if their batting colleagues performed well in the previous season. Evidence from salary regressions suggests that there are some direct links between pay and team performance, however team-mates also have an indirect effect on salary via individual performance. The latter effect is particularly noticeable for pitchers. These results suggest that workers may have impacts on the pay of their co-workers that only appear after time has passed and, as such, are overlooked by studies that analyze the effect of contemporaneous co-worker output on earnings.

APPENDIX 1

Table 3.A1
Teams used in the analysis

Team name	Abbreviation	Years in dataset
Anaheim Angels	ANA	1965-2003
Arizona Diamondbacks	ARI	1998-2003
Atlanta Braves	ATL	1966-2003
Baltimore Orioles	BAL	1954-2003
Boston Red Sox	BOS	1953-2003
Brooklyn Dodgers	BRO	1953-1957
Chicago Cubs	CHN	1953-2003
Chicago White Sox	CHA	1953-2003
Cincinnati Reds	CIN	1953-2003
Cleveland Indians	CLE	1953-2003
Colorado Rockies	COL	1993-2003
Detroit Tigers	DET	1953-2003
Florida Marlins	FLO	1993-2003
Houston Astros	HOU	1962-2003
Kansas City Athletics	KC1	1955-1967
Kansas City Royals	KCA	1969-2003
Los Angeles Dodgers	LAN	1958-2003
Milwaukee Braves	ML1	1953-1965
Milwaukee Brewers	MIL	1970-2003
Minnesota Twins	MIN	1961-2003
Montreal Expos	MON	1969-2003
New York Giants	NY1	1953-1957
New York Mets	NYN	1962-2003
New York Yankees	NYA	1953-2003
Oakland Athletics	OAK	1968-2003
Philadelphia Athletics	PHA	1953-1954
Philadelphia Phillies	PHI	1953-2003
Pittsburgh Pirates	PIT	1953-2003
San Diego Padres	SDN	1969-2003
San Francisco Giants	SFN	1958-2003
Seattle Mariners	SE1	1977-2003
Seattle Pilots	SEA	1969-1969
St Louis Browns	SLA	1953-1953
St Louis Cardinals	SLN	1953-2003
Tampa Bay Devil Rays	TBA	1998-2003
Texas Rangers	TEX	1972-2003
Toronto Blue Jays	TOR	1977-2003
Washington Nationals	WS1	1953-1960
Washington Senators	WS2	1961-1971

APPENDIX 2

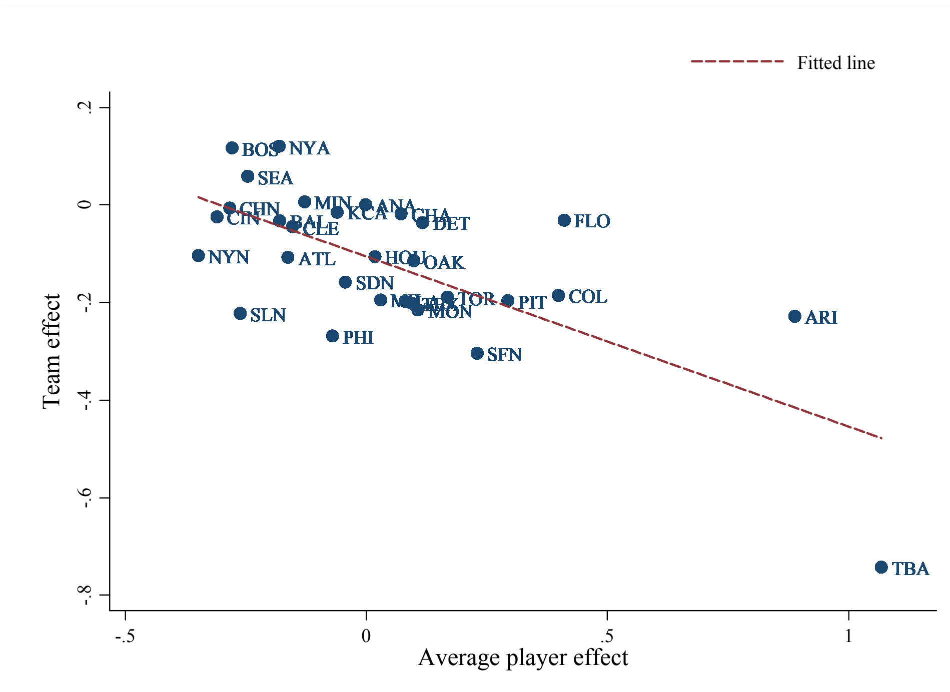

Figure 3.A1
Team effects and player effects from the salary regression for pitchers

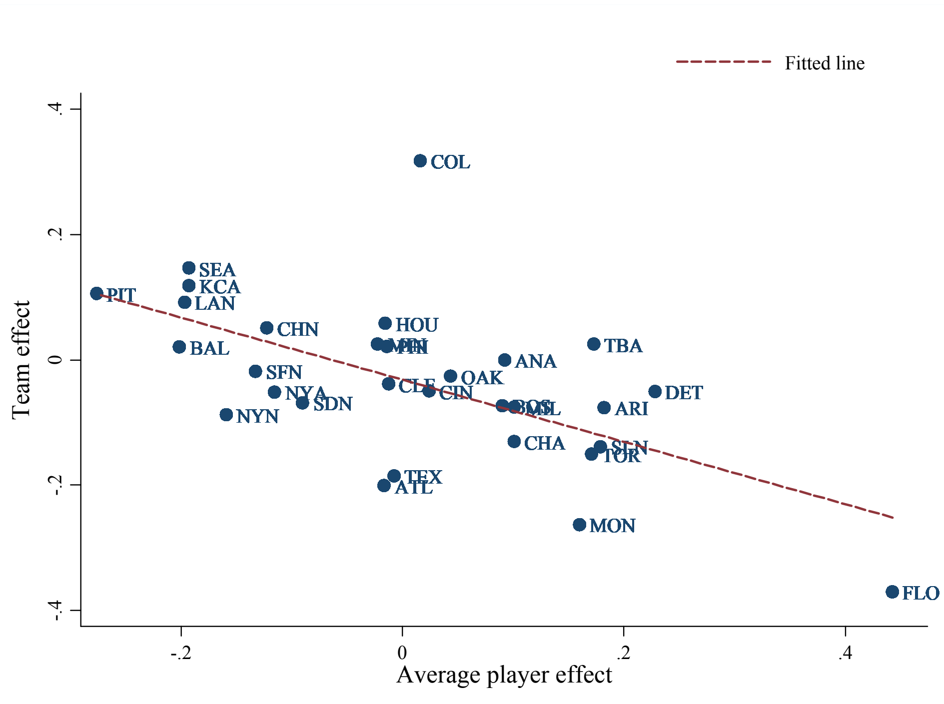

Figure 3.A2
Team effects and player effects from the salary regression for non-pitchers

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4. Job tenure and wage determination within firms

"Example is the school of mankind, and they will learn at no other."
EDMUND BURKE

Traditional theories of labor demand imply that workers' pay is determined solely by their marginal products of labor. However, there are many alternative theories that predict that one worker may influence the productivity and, hence, the wage rate of others. These effects have been termed human capital spillovers. In one well-known paper, Kremer (1993) considered a production function in which the abilities of workers enter in a multiplicative fashion. A consequence of this is that profit-maximizing firms will choose workers of identical abilities. In more sophisticated models, firms hire differently-skilled workers but pay them according to the skill mix of the other workers in the firm.

The various predictions of these theories have been largely untested before now, primarily due to the lack of datasets providing information on all workers at a set of firms. Matched employer-employee data, based on administrative records, allow the analyst to observe wage and employment records on the vast majority of workers in the economy and, hence, identify the employees at each firm. However, these data typically contain little additional demographic information on individuals, hindering their usefulness for studies of human capital spillovers.

This paper aims to determine whether a person's ability affects the wages of his co-workers and, if so, *which* co-workers. Linked employer-employee data from the United States Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) program are used. This includes information on what quarters a person was employed in a particular job, meaning that job tenure can be calculated for all jobs that begin after the first quarter in the dataset. However, since the dataset does not include retrospective information on when each worker began his/her job, tenure is left-censored at the point where each state enters the program. In this paper, the missing values on job tenure are imputed by drawing on data from the Survey of Income and Program Participation (SIPP).

Using the completed tenure variable, along with a previously-imputed education variable, a set of wage regressions is then estimated. The average education level and tenure within each firm are both found to have a positive effect on workers' earnings, *ceteris paribus*, indicating the existence of intra-firm human capital spillovers. These effects are stronger among women than among men. Furthermore, the interaction of own tenure and firm tenure is found have a negative effect on wages, suggesting that new entrants are most influenced by the average experience of their colleagues. In contrast, the interaction of own and firm education is found to have a positive impact on wages, implying that highly-educated workers benefit most from an increase in the education level within a firm.

The next section reviews the literature on intra-firm human capital spillovers, followed by a discussion of the data sources used in this project and how they are combined with one another. Section 3 explains the method that is used to impute values for each person's initial tenure where it is missing. Using the completed tenure variable, Section 4 presents some basic wage regressions for men and women using a 5% random sample of workers from the 25 states in the LEHD data.

1. Literature review

A seminal paper on intra-firm productivity spillovers was by Rosen (1982). This formalized an earlier model of Mayer (1960), while adopting a production function that is similar to that of Lucas (1978). His model relies on a hierarchical description of firms, whereby workers at each "level" of the operation are responsible for monitoring the efforts of workers at the level immediately below them.[1] By doing so, they increase the output of their subordinates by an amount that is dependent on the individual's skill, thereby creating human capital externalities. A worker *i* in the bottom-level production activity is assumed to have productivity q_i. A manager *j* in the next tier up is assumed to have skill r_j and to devote time t_i to monitoring production worker *i*. This individual's total output is then assumed to be given by:

$$X_j = g(r_j)\sum_i f(rt_i, q_i) . \tag{4.1}$$

Management skill *r* can be viewed as an intra-firm public good, insofar as it increases the productivity of all subordinates, irrespective of their numbers. A manager with skill *s* at the third level oversees multiple second-level workers and, hence, has output:

$$Y = \sum_j G(s)F(sv_i, X_j) . \tag{4.2}$$

All higher management levels are analogous. Each person is assumed to have a profile of "latent" skills: $(q, r, s, ...)$. Rosen assumes that the various skill components are positively correlated for each individual and are determined by a single random variable, ξ.

A two-level firm has a production function defined by the following maximization problem:

$$X = H^n(r, T, q_1, q_2, ..., q_n) = \max_{t_i} \{\sum_i g(r)f(rt_i, q_i) + \lambda(T - \sum_i t_i)\} . \tag{4.3}$$

In general, the solution to this will comprise a production function that features each q_i as a factor of production. Hence, the size and skill composition is important. However, if *f* exhibits constant returns to scale, so that $f(rt, q) = q\theta(rt/q)$,

[1] Although Rosen considered monitoring of subordinate workers to be the mechanism via which human capital spillovers are propagated, he conceded that it admits other interpretations. Kremer and Maskin's (1996) work suggests that this may simply be viewed as different tasks within firms being complementary in production.

equilibrium production is found to depend only on the total amount of production labor controlled, Q, not on the number or skill distribution of production workers:

$$X = \sum_i q_i g(r)\theta(\frac{tT}{Q}) = g(r)Q\theta(\frac{rT}{Q}). \tag{4.4}$$

In this case, production workers are perfect substitutes. Given a competitive labor market, Q should be chosen to satisfy:

$$g(r)(\theta(\frac{r}{Q}) - \frac{r}{Q}Q\theta'(\frac{r}{Q})) = \frac{w}{p}. \tag{4.5}$$

Comparative statics reveal that both production labor hired and output produced rise more than proportionately with managerial talent, r. Constant returns to scale implies that the case of multi-level firms is a simple extension of the above analysis. Firms can be disassembled to any number of ranks, implying that in equilibrium every manager would receive the same income regardless of how many ranks were "above" him.

Kremer (1993) developed a theory in which production is subject to "mistakes" in any of several tasks. Expected production can be written as follows:

$$E(y) = k^\alpha (\prod_{i=1}^{n} q_i)nB, \tag{4.6}$$

where k is capital, n is the number of tasks, q_i is the expected percentage of maximum value the product retains if a worker performs task i and B is output per worker with a single unit of capital if all tasks are performed perfectly. The firm's objective function is:

$$\max_{k,q} k^\alpha (\prod_{i=1}^{n} q_i)nB - \sum_{i=1}^{n} w(q_i) - rk. \tag{4.7}$$

Kremer notes that a necessary condition for any solution is that q be the same for all workers within a firm. He concludes that the set of wage schedules consistent with the first order conditions from Equation 4.7 are given by:

$$w(q) = (1-\alpha)q^n Bk^\alpha + c, \tag{4.8}$$

where c represents the wage of a worker who never performs a task successfully. The zero profit condition implies that $c = 0$. Kremer notes that the equilibrium level of n (which is presumably related to firm size) must satisfy the following condition:

$$-\ln q = \frac{B'(n)}{B(n)}. \tag{4.9}$$

He also examines the effect of endogenizing skill, by treating it as the product of investment in education, and of allowing for imperfect matching between workers and firms.

Kremer and Maskin (1996) extend the so-called O-ring theory and develop a model in which workers are imperfect substitutes. They use a simple production function, which is based on the following:

$$f(q, q') = qq'^{\alpha}, \tag{4.10}$$

where q and q' are the skills of two workers hired for two separate tasks (*e.g.* management and production) and $\alpha > 1$. The authors note that, under the constant returns to scale assumption, Lucas's and Rosen's production functions allow no substitution of skill at the management level but perfect substitution at the production level. On the other hand, their production function imposes imperfect substitutability on subordinates as well as managers.

A similar model to Kremer (1993) is presented by Saint-Paul (2001). This allows for a more general pattern of human capital spillovers than the O-ring theory, although it does not take into account the hierarchical nature of workplaces. In Saint-Paul's model, firm k's output is equal to $a(\bar{y}_k)$, where $\bar{y}$ is the average skill level of its workers. There is a mass 1 of workers and each firm consists of a mass s of workers. The equilibrium wage schedule is shown to be:

$$w(y) = \frac{a(\bar{y}_k)}{s} + \frac{a'(\bar{y}_k)(y - \bar{y}_k)}{s}, \tag{4.11}$$

if firm k employs some workers of type y. This equation clearly demonstrates how a worker's wage is directly affected by co-workers' levels of human capital. Saint-Paul demonstrates that each firm's equilibrium wage schedule is linear and the overall wage schedule is convex.[2] There may or may or not be segregation of differently-skilled workers. Since all spillovers are internalized by firms and reflected in the wage structure, the equilibrium is efficient.

Very few empirical studies have examined the existence of intra-firm productivity spillovers, primarily due to the paucity of datasets that allow the researcher to assess the quality of an individual's co-workers.[3] Battu *et al*. (2003) and Metcalfe and Sloane (2007) both used data from the British Workplace Employee Relations Survey to estimate the effect co-workers' education has on earnings. This dataset has establishment-level information for over 2,000 British workplaces with at least five workers, along with individual-level information for 25 randomly-selected workers at each establishment. Battu *et al*. regressed log earnings on own education and average co-worker education, as well as the interaction of these terms or a measure of workplace educational dispersion. Spillover effects were found to have a positive effect on earnings and this was independent of a worker's own education. However, they found no support for Kremer's (1993) hypothesis that co-worker education has the largest impact on wages when workers have a uniform level of education. Furthermore, there was no evidence that co-worker effects are strongest in high-skilled workplaces, thus rejecting the notion of increasing returns to human capital. Metcalfe

[2] Specifically, two firms either offer the same wage schedule or they obey a sorting property, whereby the most skilled worker at one firm is less skilled than the least skilled worker at the other firm.

[3] There have, however, been many studies of human capital spillovers at the regional level. For example, Rauch (1993) used 1980 United States Census data and concluded that the average level of human capital is a local public good. Moretti (2002) also found evidence of productivity spillovers within detailed city/industry cells, combining data from the Censuses of Manufacturers and Population. On the other hand, Rudd (2000) used Current Population Survey data and found little evidence that the average level of human capital in a region affects the earnings of individuals in that region, independent of their own characteristics.

and Sloane also concluded that workplace education and training have positive effects on hourly pay. In addition, they found that the interaction of own and co-worker education had a negative impact on wages, while the interaction of own and co-worker training had a positive impact.

Using linked employer-employee data from the LEHD program, Abowd *et al*. (2002) examined the relationship between firm-level measures of workforce human capital and productivity and the market value of the firm. They note that production functions may give rise to interaction effects across the skills of co-workers and discuss Kremer and Maskin's (1996) conclusion that if this interaction effect reflects complementarities across skill groups at the firm, then businesses with lower skill dispersion will be more productive. Their empirical results are consistent with the existence of complementarities across co-workers that differ on different dimensions of skill, although they are unable to test between competing explanations.

Only one previous empirical study has explicitly examined the effect of human capital externalities at the intra-firm level in the United States. Lengermann (2002) analyzed linked employer-employee data from the LEHD program for Illinois over the period 1990 to 1998. Although these data crucially allow the researcher to observe the wages of one's co-workers, they suffer from a dearth of demographic variables. As a consequence, Lengermann relied on the measured person effects as a proxy for co-worker skills. He modified the basic Abowd *et al*. (1999) specification to include co-worker attributes as follows:

$$y_{it} = \mathbf{X}_{it}\boldsymbol{\beta} + \mathbf{W}_{ijt}\mathbf{X}_{jt}\boldsymbol{\lambda}_1 + \theta_i + \mathbf{W}_{ijt}\boldsymbol{\theta}_{jt}\lambda_2 + \psi_j + u_{it}; \tag{4.12}$$

$$u_{it} = \mathbf{W}_{ijt}u_{jt}\lambda_3 + \varepsilon_{ijt}, \tag{4.13}$$

where $\mathbf{W}_{ijt}$ is a row vector of co-worker weights, $\mathbf{X}_{jt}$ is a matrix of worker characteristics in firm *j* at time *t* and $\boldsymbol{\theta}_{jt}$ is a vector of person effects for workers in firm *j* at time *t*. The co-worker effects are assumed to be captured by $\boldsymbol{\lambda}_1$, λ_2 and λ_3.

Since the θ terms are not known *ex ante*, Equation 4.12 must be estimated by an iterative process.

Although co-worker effects were found to be quantitatively less important than individual and firm effects, there was considerable variation across industries. Lengermann found that a one standard deviation increase in both a firm's average person effect and experience level yields wage increases of 3-5% on average. Industry average co-worker effects were found to explain 26% of observed inter-industry wage differentials.

2. Data

The primary data used in this project are taken from the so-called Snapshot files, which are an edited version of the Quarterly Workforce Indicators (QWI) production and infrastructure files. These have been constructed by the LEHD program at the United States Census Bureau using administrative data provided by state agencies, enhanced with information from other administrative data sources, demographic and economic surveys and censuses. Complete Snapshot files are currently available for 25 states. These contain data from the quarter the state entered the LEHD program to either the final quarter of 2003 or the first or second quarter of 2004. Full details are provided in the appendix. Three sets of files from the Snapshot are used in this analysis: the Employment History Files (EHFs), Individual Characteristics Files (ICFs) and Employer Characteristics Files (ECFs). Full details of these are given in Abowd *et al*. (forthcoming).

The EHFs contain the complete in-state work history for each individual that appears in the state unemployment insurance (UI) wage records. The EHF for each state contains one record for each employee-employer combination (a job) in that state in each year. An active job within a quarter is defined as having strictly positive quarterly earnings for the individual-employer pair that define the job. Both annual and quarterly earnings variables are available in the EHF and each person is identified by a Protected Identification Key (PIK), while each firm is identified by a State Employer Identification Number (SEIN).

The ICF for each state contains one record for every person who is ever employed in that state over the time period spanned by the state's UI records. Each person is identified by a PIK. Variables include a person's date of birth, sex, place of residence, education level, race, place of birth and citizenship status. Sex and age information from the CPS is used to complement and verify the UI information.

The ECF consolidates most employer and establishment-level information into two files. This paper uses the employer-level file, which contains one record for every quarter in which an SEIN is present in the wage records. Variables include the employer's size, payroll, location, industry and number of establishments.

Although the Snapshot files allow the researcher to identify whether a worker began or finished a job in a given quarter, they do not contain information on how long a person had held a job in the first period the data were reported.[4] In contrast, the SIPP contains detailed information on each respondent's entire job history. Hence, data from the SIPP can be used to impute a variable containing a person's tenure in his current job.

The SIPP sample is a multistage stratified sample of the U.S. civilian non-institutionalized population. It consists of a continuous series of national panels, with sample size ranging from approximately 14,000 to 36,700 interviewed households. For the 1990-1993 panels, a panel of households was introduced each year in February. A

[4] As noted in the appendix, different states entered the LEHD program at different times, meaning that this initial period varies.

four-year panel was introduced in April 1996. The SIPP contains a detailed set of questions about labor force participation, program participation and income.

This project utilizes a cleaned-up set of confidential SIPP data files constructed from the 1990-1993 and 1996 panels by Martha Stinson at the Census Bureau. For each cohort of the SIPP, there are two files: a job-level file, which contains a set of variables containing information about every job held by SIPP respondents, including the SIPP ID for the person and the SEIN of the employer and a person-level file, containing detailed information about the person. There is also a "cross-walk" file, matching the SIPP person ID to a PIK, which is used in the Snapshot files.

By merging together the ECF, EHF and ICF files for each state, a set of job-quarter-level files were created, containing each person's sex, race, age, education level, earnings from wages and salary, foreign born status and the industry and payroll of his/her employer. Here, a "job" is taken to mean a unique combination of PIK and SEIN. A job start date variable is constructed, based on the first year that a job is observed. Where this is the period the state entered the LEHD program, the job start date is assumed to be missing.

The SIPP file is merged with the Snapshot dataset on a state-by-state basis, using the PIK to match individuals and the SEIN to distinguish between their job records.[5] Only records with missing job start dates (*i.e*. left censored observations) are kept and the job-quarter-level dataset is converted to a job-level dataset. 20.34% of the jobs had start dates in the SIPP that were *later* than the quarter a state entered the LEHD data. In these cases, the job was assumed to have begun in the first quarter in the dataset, *i.e*. the job tenure was zero.

[5] This is achieved by first merging the PIK into the SIPP file from the SIPP crosswalk file. The SEIN is then merged in from the ECF using the PIK, EIN and year (since EIN can change over time in the Snapshot data) to match observations.

Table 4.1
Characteristics of the matched SIPP/LEHD data

Variable	Number of observations in SIPP data	Percentage with same value in LEHD data
Sex	40,741	99.39
Year of birth	40,745	90.32
Industry (SIC division)	22,816	79.33
Born outside US	27,172	92.74
State of birth (US born only)	20,206	92.31

Notes: The third column reports the percentage of the observations in the second column that match exactly on the variable in the first column.

Table 4.1 provides some information about how well the SIPP records match the LEHD data. Among the SIPP observations that are matched to the LEHD data and have valid information on sex, almost all have the same value of sex in the LEHD data. Similarly, year of birth and birthplace match closely between the two data sources. Industry group matches somewhat less well, which is perhaps understandable, given that the SIPP data are based on self-reported information. This suggests that in the vast majority of cases the correct job has been linked between the SIPP and LEHD data.[6]

To ascertain whether the SIPP job start date matches well with the first date a job is observed in the LEHD data, a validation exercise was undertaken. Maryland is unique in that it has EHF information from 1985 onwards (see appendix), although ECF data are only available from 1990. This means that even though the data start period for the purposes of this study is 1990, information on job spells in the LEHD data that began up to five years earlier is available and can be compared with the corresponding SIPP information. Of the 424 job observations from the SIPP that were matched to the Maryland Snapshot data, 44% had exactly the same start quarter in both datasets, while 59% differed by no more than one quarter. 83% had a start quarter

[6] Note that the sex, date of birth, industry and place of birth information from the SIPP will not be used elsewhere in this project – the corresponding variables from the LEHD data will be used instead.

that was no more than one calendar year apart in the SIPP and LEHD datasets. There was no significant difference between the match rates for men and women, nor between those aged under 30 and those aged at least 30.

3. Imputation approach

Using the merged job-level dataset, an imputation model for initial tenure (in quarters) is developed. Since there is a spike at zero quarters, tenure is modeled by two variables: a dummy variable for whether the person worked zero quarters and the number of quarters the person worked if it is greater than zero. The latter only takes non-missing values when the former is zero. Sequential Regression Multivariate Imputation (SRMI) is used to complete these two variables.

The data, **Y**, are partitioned as follows:

$$\mathbf{Y} = (\mathbf{Y}_{mis}, \mathbf{Y}_{obs}) . \tag{4.14}$$

In this study, $\mathbf{Y}_{mis}$ includes the two tenure variables, while $\mathbf{Y}_{obs}$ includes age, payroll in the firm, seven dummies for race/ethnicity, three dummies for foreign born status, ten dummies for industry and 24 dummies for state of employment.[7]

The missing data matrix **M** is dimension $N \times 2$ and consists of zeros for non-missing observations and ones for missing observations.

We are interested in the joint distribution of these matrices, which can be written as:

$$p(\mathbf{Y}_{mis}, \mathbf{Y}_{obs}, \mathbf{M}, \boldsymbol{\theta}, \boldsymbol{\psi}) = p(\mathbf{M} \mid \mathbf{Y}_{mis}, \mathbf{Y}_{obs}, \boldsymbol{\psi}) p(\mathbf{Y}_{mis}, \mathbf{Y}_{obs} \mid \boldsymbol{\theta}) , \tag{4.15}$$

[7] The race/ethnicity categories are: not classified; white; black; American Indian; Asian/Pacific Islander; Hispanic (any race); and multiple races. The foreign born status categories are: born in the United States; born abroad to American parents; and born abroad to non-American parents. The industry categories are the SIC divisions, namely: agriculture, forestry and fishery; mining; construction; manufacturing; transportation; communications; electric, gas and sanitary services; wholesale trade; finance; insurance and real estate; services; and public administration.

where $\boldsymbol{\psi}$ and $\boldsymbol{\theta}$ are parameters associated with the missing data mechanism and complete data model, respectively. SRMI requires that Bayesian ignorability be assumed, in other words that the data are both missing at random:

$$p(\mathbf{M} \mid \mathbf{Y}_{mis}, \mathbf{Y}_{obs}, \boldsymbol{\psi}) = p(\mathbf{M} \mid \mathbf{Y}_{obs}, \boldsymbol{\psi}), \tag{4.16}$$

and that the joint distribution of the parameters may be factorized:

$$p(\boldsymbol{\theta}, \boldsymbol{\psi}) = p(\boldsymbol{\theta}) p(\boldsymbol{\psi}). \tag{4.17}$$

The predictions of the missing data from SRMI are then obtained by sampling from the following conditional density:

$$p(\mathbf{Y}_{mis} \mid \mathbf{Y}_{obs}) = \int p(\mathbf{Y}_{mis} \mid \mathbf{Y}_{obs}, \boldsymbol{\theta}) p(\boldsymbol{\theta} \mid \mathbf{Y}_{obs}) d\boldsymbol{\theta}, \tag{4.18}$$

which is equivalent to:

$$p(y_1, y_2, \ldots y_K \mid \theta_1, \theta_2, \ldots, \theta_K) = p_1(y_1 \mid \theta_1) p_2(y_2 \mid y_1, \theta_2) \ldots \\ p_K(y_K \mid y_1, \ldots, y_{K-1}, \theta_K). \tag{4.19}$$

The procedure consists of L regression rounds. In this case, L was set equal to 4. In round $l+1$, missing values of y_k are drawn from the conditional density:

$$p_k(y_k \mid y_1^{l+1}, y_2^{l+1}, \ldots, y_{k-1}^{l+1}, y_{k+1}^{l}, \ldots, y_K^{l}, \theta_k), \tag{4.20}$$

where y_k^l denotes the completed data in round l for variable y_k, p_k is specified by an approximate linear model and θ_k are the parameters of that model. Hence, at round l, the variable under imputation is regressed on all non-missing data and the most recently-imputed values of missing data. Here, linear regression is used for the log of number of quarters and logit is used for the zero quarters dummy variable.

In practice, data are stratified in order to achieve more homogenous groups of observations and the SRMI procedure is repeated on each stratum separately. Where cells sizes become too small, strata are combined. In this case, the data were initially stratified by sex, the decile of people's average real quarterly income (in 2000 dollars) over the remainder of their job tenure and the decile of the number of remaining quarters they spent on the job. These were collapsed to quintiles where necessary. The minimum cell size was set to 1500 observations.

An SRMI routine that was written for SAS by Gary Benedetto and Simon Woodcock was used. This allowed the continuous tenure variable to be constrained to be greater than zero but less than the maximum job tenure observed in the SIPP data as of the initial Snapshot period (262 quarters) *and* less than the number of quarters since the person was 15. The logarithm of the number of quarters was used in the imputation procedure in order to more closely approximate normality; the variable was untransformed after the procedure and rounded to the nearest integer. This routine uses the Bayes Information Criterion to determine which regressors to include in each regression.[8]

Table 4.2 shows the distribution of the imputed tenure values (*i.e*. those for the first quarter each state appears in the UI data) alongside the distribution of the complete SIPP tenure variable and the distribution of the uncensored LEHD values in the sample that will be used for the regressions in the next section. As noted earlier, there is a spike at zero quarters in the SIPP data. Otherwise, the LEHD complete data features a greater number of short job spells. This is not surprising, since only those jobs from the SIPP that are matched to the LEHD are included here. In most cases, the source year of the SIPP information is later than the year each state entered the LEHD dataset. That means that short job spells from the SIPP are not captured. The distribution of tenure in the imputed dataset is slightly different from the original SIPP data. This is due to it having a different distribution of the stratifying and conditioning variables used in the imputation model. When cells with the same characteristics are compared, the distributions look very similar.

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[8] Regressors are dropped if their *t*-statistics are less than $\sqrt{\ln(N)/2}$, where N is the number of observations.

Table 4.2
Distribution of tenure in complete and imputed data

Tenure (in quarters)	SIPP data (%)	LEHD imputed data (%)	LEHD complete data (%)
Men			
0	26.20	29.75	22.63
1-3	10.41	11.45	31.36
4-7	8.93	12.97	18.27
8-19	16.47	20.28	20.31
20-39	14.35	13.39	6.83
40 or more	23.64	12.16	0.60
Number of observations	20,349	41,554,058	74,707,034
Women			
0	24.74	29.20	21.62
1-3	11.68	12.41	31.54
4-7	10.53	14.13	18.86
8-19	18.45	21.10	20.71
20-39	15.15	12.83	6.71
40 or more	19.45	10.33	0.56
Number of observations	18,872	37,546,454	70,101,968

Notes: The LEHD imputed data include every observation from the first quarter a state entered the LEHD dataset; the LEHD complete data include observations for all jobs that began after the first quarter, for the 5% random sample only.

4. Some results

Having imputed missing initial values for tenure in the LEHD data, it is now possible to use this variable in analyses. For jobs that began after a state entered the dataset, tenure (in quarters) can be calculated exactly – this is the number of quarters a person has received positive earnings from a firm (defined by SEIN). For jobs that began before or during the first quarter of the LEHD data for a state, tenure would be imputed. In practice, M implicates of the completed tenure variable would be constructed and then merged into a job-quarter-level dataset. All means and regression estimates would then be averaged over the M implicates and standard errors would reflect the fact that there is variation both within and between the implicates.

Table 4.3 reports the results of log wage regressions using the completed tenure variable for men aged 15-64. Quarterly observations for each of the 25 states in the

Table 4.3
Log wage regressions for men

Variable	(i)	(ii)	(iii)	(iv)
Age (in years)	0.151*	0.193*	0.192*	0.189*
	(0.000)	(0.000)	(0.000)	(0.000)
Age squared	-0.002*	-0.002*	-0.002*	-0.002*
	(0.000)	(0.000)	(0.000)	(0.000)
Tenure (in quarters)	0.030*	0.019*	0.017*	0.018*
	(0.000)	(0.000)	(0.000)	(0.000)
Tenure squared	-0.000*	-0.000*	-0.000*	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Average co-worker education			0.103*	0.070*
			(0.000)	(0.000)
Average co-worker tenure			0.004*	0.006*
			(0.000)	(0.000)
Education × average co-worker education				0.002*
				(0.000)
Tenure × average co-worker tenure				-0.000*
				(0.000)
Person effects	No	Yes	Yes	Yes
R-squared	0.290	0.686	0.690	0.690
Number of observations	61,928,653	61,928,653	61,928,653	61,928,653

Notes: Standard errors are presented in parentheses. * denotes significance at the 1% level.

LEHD dataset are included up to the final quarter of 2003. To reduce computational requirements, a 5% random sample of workers was taken for each state.[9] In addition, as a preliminary analysis, only one implicate of initial tenure was used. Observations from firms with fewer than 5 workers are dropped and quarterly earnings observations less than \$250 or more than \$250,000 (in 2000 dollars) are also excluded. The full specification to be estimated is similar to that used by Metcalfe and Sloane (2007):

$$\ln w_{it} = \beta_0 + \beta_1 A_{it} + \beta_2 A_{it}^2 + \beta_3 \tau_{it} + \beta_4 \tau_{it}^2 + \beta_5 E_{it} + \beta_6 T_{it} + \beta_7 e_i E_{it} + \beta_8 \tau_{it} T_{it} + \theta_i + \varepsilon_{it}, \quad (4.21)$$

where w_{it} is the earnings received by person *i* in quarter *t*, A_{it} is the person's age in years, τ_{it} is job tenure in quarters, e_i is years of schooling, E_{it} is the average years of

[9] Observations from all jobs and all quarters for the selected workers are used.

schooling in the person's workplace, T_{it} is the average tenure in the workplace and θ_i is a person effect, which is treated here as a fixed effect.

In the first column, the only regressors are age and tenure and their squares. Log wages are found to be concave in both age and tenure. At the mean, a one year increase in age results in a 2.8% increase in quarterly earnings, while a one quarter increase in job tenure yields a 2.4% increase. The estimated coefficients imply that, on average, men experience increasing wages until they have worked at a firm for 20 years, while the effect of age becomes negative after 45. When person effects are introduced in the second column of Table 4.3, the wage-age profile becomes slightly steeper, while the wage-tenure profile flattens.

In the third column of Table 4.3, the average education level and tenure across all workers in an individual's workplace are added as regressors. These variables are calculated separately for each quarter. Both are found to have a positive effect on an individual's wage, suggesting that positive human capital spillovers do occur within firms. A one year increase in the average education level within a firm will increase a worker's wage by 10.3%, while a one year increase in the average tenure will increase the wage by 1.5%, *ceteris paribus*. The estimated coefficient on co-worker education is remarkably similar to the 12% found by Metcalfe and Sloane (2007) in the United Kingdom, despite the fact that many fewer additional factors are controlled for here.

To examine whether the effect of co-worker ability differs across individuals, the final column of Table 4.3 adds as regressors the interaction of individual education and average firm education and the interaction of individual tenure and average firm tenure. The education interaction term is found to have a positive coefficient and indicates that the wage effect of co-worker education varies between 7.0% for men with no education and 11.1% for men with a college degree (*i.e.* 17 years of schooling). This result contrasts with that of Metcalfe and Sloane, who found a

Table 4.4
Log wage regressions for women

Variable	(i)	(ii)	(iii)	(iv)
Age (in years)	0.147*	0.210*	0.200*	0.197*
	(0.000)	(0.000)	(0.000)	(0.000)
Age squared	-0.002*	-0.002*	-0.002*	-0.002*
	(0.000)	(0.000)	(0.000)	(0.000)
Tenure (in quarters)	0.043*	0.029*	0.026*	0.029*
	(0.000)	(0.000)	(0.000)	(0.000)
Tenure squared	-0.000*	-0.000*	-0.000*	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Average co-worker education			0.195*	0.105*
			(0.000)	(0.001)
Average co-worker tenure			0.008*	0.011*
			(0.000)	(0.000)
Education × average co-worker education				0.007*
				(0.000)
Tenure × average co-worker tenure				-0.000*
				(0.000)
Person effects	No	Yes	Yes	Yes
R-squared	0.216	0.564	0.573	0.573
Number of observations	65,514,365	65,514,365	65,514,365	65,514,365

Notes: Standard errors are presented in parentheses. * denotes significance at the 1% level.

negative interaction effect for education, which they interpreted as evidence of an "intra-workplace competitive effect". The tenure interaction term has a negative coefficient. This implies that average co-worker tenure has a *negative* effect on earnings for those individuals who have worked at a firm for more than 11 years.

Table 4.4 repeats the analysis for women in the twenty-five state sample. The earnings-tenure profile is found to be slightly steeper than for men. Both co-worker tenure and co-worker education have larger effects on women's earnings than on men's. In addition, the interaction of workplace education with individual education is noticeably larger than among men. Average co-worker education has a 10.5% effect on the earnings of women with no schooling, compared with a 21.7% effect on the earnings of women with college degrees. As with men, co-worker tenure has a negative effect after 11 years of employment at a firm.

5. Conclusion

This paper has outlined a procedure to complete missing values for job tenure in the matched employer-employee data that has been developed by the United States Census Bureau. This used sequential regression multivariate imputation and drew on retrospective job start date information contained in the Survey of Income and Program Participation. The completed tenure variable, along with years of education, was used in a set of wage regressions. Both variables were found to have a concave relationship with earnings. To examine the effects of co-worker ability on an individual's earnings, the average education and tenure within each firm were added as regressors. Both were found to have a positive impact on wages, with larger coefficients for women. When the interaction of own and firm tenure was added to the regression, it was revealed that the wage effects of average tenure are strongest for new hires in a firm. In contrast, the strongest effect of average education on pay is experienced by the highest-educated workers in a firm.

The regressions presented in this paper represent a first attempt to examine the effects that co-worker experience have on earnings. Future work will extend the basic specification of the wage equation. Firm effects will be added, as in the specification of Abowd *et al*. (1999). In addition, a modification of the approach taken by Lengermann (2002) could be used. As noted earlier, Lengermann used an iterative procedure, whereby he calculated the average of the person effects across each firm in one stage and included it as a regressor in the next stage. An alternative approach would be to calculate either a *weighted* average of the person effects within the firm or to average across only certain workers. For example, the average person effect among only those earning above or below a certain threshold could be calculated and included in a regression. By determining how closely these variables are related to individual wages, this would provide evidence of whether the models such as those of Rosen (1982) and Kremer (1993) hold.

APPENDIX

Table 4.A1
States in the LEHD data

State	Abbreviation	ICF quarters	EHF quarters	ECF quarters
California	CA	1991iii-2003iv	1991iii-2003iv	1991i-2003iv
Colorado	CO	1990i-2004i	1990i-2004i	1990i-2004i
Florida	FL	1992iv-2004i	1992iv-2004i	1989i-2004i
Idaho	ID	1990i-2004i	1990i-2004i	1991i-2004i
Illinois	IL	1990i-2004i	1990i-2004i	1990i-2004i
Indiana	IN	1990i-2004i	1990i-2004i	1998i-2004i
Iowa	IA	1998iv-2004i	1998iv-2004i	1990i-2004i
Kansas	KS	1990i-2004i	1990i-2004i	1990i-2004i
Kentucky	KY	1996iv-2004i	1997i-2004i	2001i-2004i
Maine	ME	1996i-2004i	1996i-2004i	1996i-2004i
Maryland	MD	1985ii-2004ii	1985ii-2003iv	1990i-2004i
Minnesota	MN	1994iii-2003iv	1994iii-2003iv	1994iii-2003iv
Missouri	MO	1990i-2004i	1990i-2004i	1990i-2004i
Montana	MT	1993i-2004i	1993i-2004i	1993i-2004i
New Jersey	NJ	1996i-2004i	1996i-2004i	1995i-2004i
New Mexico	NM	1995iii-2004i	1995iii-2004ii	1990i-2004i
North Carolina	NC	1991i-2003iv	1991i-2003iv	1990i-2003iv
Oklahoma	OK	2000i-2004i	2000i-2004ii	1999i-2004i
Oregon	OR	1991i-2004i	1991i-2004i	1990i-2004i
Pennsylvania	PA	1991i-2004i	1991i-2004i	1991i-2004i
Texas	TX	1995i-2003iv	1995i-2003iv	1990i-2003iv
Virginia	VA	1998i-2004i	1998i-2004i	1995iii-2004i
Washington	WA	1990i-2004i	1990i-2004i	1990i-2004i
West Virginia	WV	1997i-2004i	1997i-2004i	1990i-2004i
Wisconsin	WI	1990i-2004i	1990i-2004i	1990i-2004i

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5. Conclusion

This dissertation has uncovered evidence that individuals' levels of human capital are not determined solely by their own actions, as is implicitly assumed by most models of education and labor supply, but are influenced by the decisions of those people they live and work with. In Chapter 2, it was shown that married women, but not men, respond to changes in the risk of divorce by increasing the hours they spend in the labor market, possibly with the aim of improving their future job prospects in the event of separation. In Chapter 3, evidence was reported suggesting that professional baseball players experience both transitory and permanent increases in productivity from having talented team-mates. Similar productivity spillovers were found to exist in the wider labor market in Chapter 4, where it was seen that, *ceteris paribus*, workers earn higher wages when their colleagues have higher levels of education or experience. These effects are largest for the highest-educated but least-experienced workers.

Overall, these findings indicate the need to take account of the effects labor market policies have on productivity levels across the economy as a whole. Changing demographics and social trends may make this an even more important issue in the future. If the divorce rate continues to fall, it is likely to become increasingly difficult to entice more married women into the labor market and wages may need to rise faster to compensate. At the same time, the move towards work at non-standard hours and at home may reduce the degree of productivity spillovers between co-workers within a firm.

Future work should address exactly who experiences productivity spillovers and what specific skills they acquire as a result. Using time-use data, it may be possible to examine whether men tend to invest in household-specific skills when faced with marital instability, in the same way that women devote more time to labor market work. Regarding productivity spillovers in the workplace, research should address the issue of who learns from whom. Do senior employees in a firm increase the productivity of those further down the job ladder or *vice versa*?