Labor market shocks and marriage duration

First version: October 2007

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January 22, 2008

Abstract: Are couples who have been together longer more likely to stick together in the face of adversity? This paper uses monthly data from the Survey of Income and Program Participation to investigate the impact on relationship duration of labor market shocks such as layoff, discharge for cause and disability. Using a Cox proportional hazard model, I show that generally these labor market shocks significantly increase the separation hazard. A man's getting fired has the largest impact on separation: it significantly increases the monthly hazard of separation by 38.5%, which is equivalent to increasing the annual probability of separation to 4.3% from its average of 3.1%. I then show that the impact of labor market shocks typically initially decreases and then increases with relationship duration. Assuming that a labor market shock is a signal of the value of the relationship to one's partner, the initial decrease in the effect can be explained by the fact that, as one learns more about one's partner, any new information is less likely to change one's evaluation. The subsequent increase in the impact of labor market shocks on the probability of separation can be explained by the fact that relationships change over time such that, at longer relationship durations, there is a relatively higher proportion of relationships perceived to be mediocre; thus, adding a labor market shock to the existing dissatisfaction can cause one of the partners to end the relationship.

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1 Introduction

Labor market shocks such as job loss typically have a negative impact on subsequent earnings, unemployment (Gibbons and Katz, 1991) and survival (Sullivan and von Wachter, 2006). Such shocks could also impact the probability that couples separate. Indeed, research into the dating market has shown that income is one of the strongest determinants of a woman's choosing to date a man (Hitsch et al., 2006). Thus we expect women in particular to be sensitive to labor market shocks that would affect men's earnings potential. Also, it seems that women are more likely to act on their dissatisfaction about their relationship: women are twice more likely to initiate a divorce than men (Kalmijn and Poortman, 2006). If negative labor market shocks do indeed affect marital stability, then this is something that needs to be taken into account when assessing the welfare consequences of such shocks.

There is only a very limited literature in economics that investigates the impact of labor market shocks on the probability of divorce or separation. Weiss and Willis (1997) look at the impact of unexpected wage gains on divorce and find a negative impact for men's wage gains and a positive one for women's wage gains. This evidence thus supports the idea that women prefer men with higher earning potential. Charles and Stephens (2004) find that probability of divorce increases when either spouse is laid off (with a stronger effect for men) but not when they become disabled. Moreover, a layoff has a stronger effect than a plant closing. Charles and Stephens (2004) speculate that what matters is the information conveyed by job loss about the fitness of the partner as a mate rather than purely economic factors.

There is a much larger literature in psychology that addresses marital functioning and its relationship to economic factors, even though this literature does not focus specifically on the impact of job loss. Economic stress decreases marital satisfaction, and this is in part due to worse marital functioning, i.e. worse communication and the like (Conger et al. 1999). Kinnunen and Feldt (2004) show that even in a country like Finland, where unemployment benefits are very generous, the longer the man stays unemployed the more likely the woman is to report increased conflict and decreased common interests.

This paper makes more explicit the mechanism through which spouses learn about their relationship and what a labor market shock means in this context. I argue that two broad set of factors could drive relationship dissolution. One theory suggests that, when partners form a relationship, they are uncertain about its true quality, and they learn about it over time. In this case, the relationship is an experience good (e.g. Jovanovic, 1979). Crucially, such a model in its pure form assumes that relationship quality does not change at all over time, the only thing that changes being the partners' *information about* their relationship. Such a learning model has been proposed by Svarer (2004) to explain the shape of the divorce hazard. The other reason why relationships may end is because they have changed: for example, the husband picks up drinking, or the wife no longer takes care of the children as she used to, etc. In this case, the relationship is an inspection good but changes over time (e.g. Mortensen-Pissarides, 1994). The change in relationship quality could also come from a change in preferences: e.g. the couple got together with the understanding that they would have children but the woman subsequently changes her mind about it. It is important to note here that in the pure version of this second model, it is not necessary to invoke limited information to explain why people separate after five years when they were still together after two. This paper develops a model that integrates both learning about relationship quality and changes in relationship quality over time. Using labor market shocks as signals of marital quality, I assess whether the pure learning or the pure changes model can explain the patterns of relationship dissolution.

The empirical analysis uses monthly longitudinal data on cohabiting couples from the 1990-2001 waves of the Survey of Income and Program Participation (SIPP). Using a Cox proportional hazard model, I find that the impact of getting fired on relationship dissolution is larger than the impact of getting laid off. Thus, for example, a man's getting fired increases the probability of separation by 38.5%, vs 17.8% if the man was laid off;

this amounts to the annual probability of divorce increasing to 4.3% and 3.7% respectively from its average of 3.1%. Contrary to Charles and Stephens' 2004 results, I find that the onset of disability also significantly increases the probability that a relationship ends. Since the SIPP is much larger than the PSID used by Charles and Stephens (2004), it allows me to assert with more detail the impact of labor market shocks at various relationship durations: I find that, past the first year, this impact generally increases in the first five years of the relationship. Thus, the impact of labor market shocks on relationship dissolution is very sensitive to the tenure of the relationship. This pattern, together with further empirical results, allows us to reject the pure learning model. The emprical evidence is broadly consistent with a mixed model that includes both uncertainty about relationship quality and a time-varying relationship quality.

The remainder of the paper is organized as follows. Section 2 presents a theory of marriage duration. Section 3 discusses the main empirical results. Section 4 discusses some further empirical results and robustness tests, and finally section 5 concludes.

2 Theory

2.1 Model specification

The model analyzes the decision of one of the partners in a relationship to continue that relationship or end it. From now on, to make the discussion more intuitive, I will assume that the woman is the partner who decides whether to separate. The problem is of course symmetric for the man[1] or a same-sex partner. It is assumed that individuals are matched randomly, which implicitly assumes that there are search frictions. The woman entering a new relationship does not know the exact value of such a relationship. The quality of the relationship, or match quality, is what makes the relationship valuable to the woman: monetary benefits, companionship, love, children, etc. Thus, the quality of a relationship

[1]If utility is transferable, then the woman and the man will always agree on the separation, so it does not even matter which point of view we consider.

is multi-dimensional. To simplify the modeling, I'll assume that this multi-dimensional relationship quality is reducible to a single index. The woman holds a prior belief about the distribution of quality in the population of potential relationships (partners). This prior $P(q_0)$ is normally distributed with mean $\bar{q}$ and variance σ_0^2. Denote by q_k the (true) match quality at length k. As long as the relationship continues, match quality is assumed to evolve over time according to the following AR(1) process:

$$q_k = \rho q_{k-1} + c + \epsilon_{k-1}^q \tag{1}$$

where $\epsilon_k^q \sim N(0, \sigma_p)$. c is a deterministic drift. I further assume that $\rho = 1$ and $c = 0$, so that the process is a random walk[2] . At each period, the woman observes a noisy signal of the quality of the partner. The signal of match quality is an observation z_k defined as:

$$z_k = q_k + \epsilon_k^z \tag{2}$$

where $\epsilon_k^z \sim N(0, \sigma_{obs})$. The best estimate $\hat{q}_k$ of q_k given all observations $z_1 ... z_k$ is fully determined by the Kalman filter solutions (see Arulampalam et al. (2001)).

Figure 1 summarizes the specific assumptions I make to solve the model, and the timing of the woman's decision process. At every time step[3], the woman has two possible actions a: she can continue the current relationship ($a = C$) or separate from the current partner, pay a separation cost $f(k)$, and begin a new relationship with another partner ($a = S$). The woman chooses one of these actions depending on her current belief and the length of the relationship k. Define a policy π, which gives for each belief and relationship length the action to be taken. Define the Q function $Q^\pi(\hat{q}_k, a)$ as the expected return of taking action a today and then following the policy π in the future. The value function $V^\pi(\hat{q}_k)$ gives the current and future rewards of the woman as a function of current belief, assuming that the woman follows policy π from now on. The optimal policy maximizes

[2] Assuming some slightly smaller ρ and higher c does not affect the qualitative results.

[3] I assume that the length of the relationship is limited to some length k_{max}.

$V^{\pi}(\hat{q}_k)$, and gives rise to the optimal value function $V^*(\hat{q}_k)$. The optimal action value function Q^* is defined as a function of the optimal value $V^*(\hat{q}_k)$:

$$Q^*(\hat{q}_k, C) = \hat{q}_k + \delta \sum_{\hat{q}_{k+1}} P(\hat{q}_{k+1}|\hat{q}_k) V^*(\hat{q}_{k+1}) \tag{3}$$

$$Q^*(\hat{q}_k, S) = \bar{q} - f(k) + \delta \sum_{\hat{q}_1} P(\hat{q}_1|\bar{q}) V^*(\hat{q}_1) \tag{4}$$

$$= V_{new} - f(k), \text{ where } V_{new} = \bar{q} + \delta \sum_{\hat{q}_1} P(\hat{q}_1|\bar{q}) V^*(\hat{q}_1)$$

The optimal value is given by the Bellman equation:

$$V^*(\hat{q}_k) = \max_{a \in [C,S]} Q^*(\hat{q}_k, a) \tag{5}$$

Thus, if the woman decides to continue with the current relationship, she gets the expected value of the relationship quality in the current period, plus any future rewards. If she instead decides to end the relationship, she gets the average value of a new match randomly drawn from the prior distribution plus any future rewards from that new match[4], and has to pay $f(k)$. The separation cost $f(k)$ covers the direct cost of ending the current relationship, such as a paying for a divorce lawyer. It also covers the costs of beginning a new relationship, such as fees to enroll in online dating sites. In this framework, the optimal policy followed by the woman is uniquely defined by $\tau(k)$, the belief such that the woman is indifferent between continuing and separating from her partner at relationship length k. In other terms, the threshold for separation $\tau(k)$ is defined by the equalization of Q functions for the actions "continue" (equation (3)) and "separate" (equation (4)). To compute the optimal values and policy, one uses a version of the "value iteration" algorithm, which has been shown to converge to the solution of the Partially Observed

[4]The definition of the reward function is compatible with a Nash bargaining solution where the two partners split the surplus, so that, while the relationship continues, each partner gets a fixed share. Suppose that α is the share received by the woman. The reward of the woman would then be $\alpha\hat{q}_k$ if continuing and $\alpha\bar{q}$ if separating; but this change is not substantial since it simply amounts to rescaling the distribution of match quality.

Markov Decision Problem (see Hauskrecht(2002)).

Note that the planning horizon of the woman is assumed to be infinite. This means that the woman is infinitely lived; or alternatively, the woman's retirement from the relationship market is at some date so far away in the future that given the discount factor, it does not play any role in the woman's current decisions. The model may thus not be adequate for explaining the behavior of older women.

The model developed here embeds two polar cases. If $\sigma_p = 0$, match quality is constant over the duration of the relationship. In that case, and assuming further that $\sigma_{obs} > 0$, the model is essentially identical to Jovanovic (1979): it is a model of learning about match quality, or "pure learning model". If $\sigma_{obs} = 0$ and $\sigma_p > 0$, match quality is perfectly observed but evolves over time. One example of such a model is Mortensen and Pissarides (1994), where job destruction is generated by idiosyncratic shocks to job productivity. In the context of a couple's separation, we can say that if $\sigma_{obs} = 0$ and $\sigma_p > 0$, then separation is only due to changes in relationship quality, so that we have a "pure changes model". When $\sigma_{obs} > 0$ and $\sigma_p > 0$, we have a "mixed model" with both learning and changes to relationship quality, i.e. the woman learns from noisy observations about a relationship quality that is constantly evolving. Because the small literature on relationship duration (Svarer, 2004) proposes the pure learning model as an explanation of the probability of relationship dissolution as a function of relationship length, this paper takes that model as a starting point. The question is then whether we can do better in explaining empirical data about relationship duration by adding changes in relationship quality to the pure learning model.

2.2 Learning, bad observations, and the separation hazard

The theoretical hazard of separation is the result of infinitely many women confronted with the same separation decision problem; it summarizes the average separation behavior of women over relationship lengths. One can compute the theoretical separation hazard once the threshold for separation is known. Note that at length 0, when no observation has been made yet, $\hat{q}_0 = \bar{q}$ for all matches, i.e. for all women the belief is the same as the prior. Let $p_k(\hat{q}_k)$ be the density of women who hold a belief with mean $\hat{q}_k$ at length k, given that they follow the optimal policy embodied in $\tau(k)$. The hazard of separation at length k, $h(k)$, can be computed recursively, starting at $k = 1$ and using the distributional assumptions. The initial values for the distribution of women's expected beliefs about match quality are:

$$p_0(\hat{q}_0) = \begin{cases} 1 \text{ if } \hat{q}_0 = \bar{q} \\ 0 \text{ otherwise} \end{cases} \tag{6}$$

$$p_1(\hat{q}_1) = \sum_{\hat{q}_0} p_0(\hat{q}_0) P(\hat{q}_1|\hat{q}_0) = P(\hat{q}_1|\bar{q}) \tag{7}$$

The hazard of separation at length k, $h(k)$, can then be computed recursively, starting at $k = 1$:

$$h(k) = \sum_{\hat{q}_k = \hat{q}_{min}}^{\hat{q}_k = \tau(k)} p_k(\hat{q}_k) \tag{8}$$

$$p_k(\hat{q}_k) = 0 \text{ if } \hat{q}_k \leq \tau(k) \tag{9}$$

$$p_k(\hat{q}_k) = \frac{p_k(\hat{q}_k)}{\sum p_k(\hat{q}_k)} \tag{10}$$

$$p_{k+1}(\hat{q}_{k+1}) = \sum_{\hat{q}_k} p_k(\hat{q}_k) P(\hat{q}_{k+1}|\hat{q}_k) \tag{11}$$

Equation (10) insures that the mass of women is always normalized to 1. $P(\hat{q}_{k+1}|\hat{q}_k)$, the distribution of possible beliefs at relationship duration k given the belief at $k-1$, can be computed given distributional assumptions.

If firing costs are constant or increasing with relationship duration, then the pure learning model implies that the hazard decreases to 0 as the relationship duration tends toward infinity. This is because in the limit the woman knows with certainty what the quality of the relationship is, and so only good relationships persist. If, on the other hand, match quality evolves over time (pure changes model or mixed model), then the hazard of separation never drops to 0 (unless separation costs become exceedingly high). This is because if the quality of a relationship can change, even a very good relationship can eventually become bad and be dissolved after a sequence of unfavorable changes.

Another feature that distinguishes the pure learning model from the others is the impact of a negative observation on the hazard of separation at different relationship durations. Assume that a labor market shock such as a job loss corresponds to the woman observing a bad signal of match quality. More specifically, assume that if the man experienced a negative labor market shock at relationship length k, then the woman observes $z_k < z^*$, where z^* is some low threshold. The hazard h_b given a bad observation $z_k < z^*$ is:

$$h_b(k) = \sum_{\hat{q}_k < \tau(k), \hat{q}_{k-1}} p_{k-1}(\hat{q}_{k-1}) \frac{P(\hat{q}_k | \hat{q}_{k-1}, z_k < z^*)}{P(z_k < z^* | \hat{q}_{k-1})} \tag{12}$$

$$= \sum_{\hat{q}_{k-1}} p_{k-1}(\hat{q}_{k-1}) \frac{\sum_{\hat{q}_k = \hat{q}_{min}}^{\hat{q}_k = min(g(\hat{q}_{k-1}, z^*), \tau(k))} P(\hat{q}_k | \hat{q}_{k-1})}{P(\hat{q}_k < g(\hat{q}_{k-1}, z^*))} \tag{13}$$

where the function g gives the value of $\hat{q}_k$, such that given $\hat{q}_{k-1}$, this value corresponds to the observation of z^* at period k. Indeed, $\hat{q}_{k-1}$ and z_k uniquely determine $\hat{q}_k$ given distributional assumptions.

Similarly, the hazard h_g given a relatively good observation $z_k > z^*$ is:

$$h_g(k) = \sum_{\hat{q}_k < \tau(k), \hat{q}_{k-1}} p_{k-1}(\hat{q}_{k-1}) \frac{P(\hat{q}_k | \hat{q}_{k-1}, z_k > z^*)}{1 - P(z_k < z^* | \hat{q}_{k-1})} \tag{14}$$

$$= \sum_{\hat{q}_{k-1}} I[g(\hat{q}_{k-1}, z^*) \leq \tau(k)] p_{k-1}(\hat{q}_{k-1}) \frac{\sum_{\hat{q}_k = g(\hat{q}_{k-1}, z^*)}^{\hat{q}_k = \tau(k)} P(\hat{q}_k | \hat{q}_{k-1})}{1 - P(\hat{q}_k < g(\hat{q}_{k-1}, z^*))} \tag{15}$$

where I is an indicator function.

It is important to note that for each relationship length k, these hazards are computed assuming either $z_k < z^*$ or $z_k > z^*$, *and, in both cases,* a history of observations up to

z_{k-1} that is consistent with the distributional assumptions and the optimal strategy of the woman. Panel A of Figure 2 plots the $h_b(k)$ and $h_g(k)$ under the pure learning model, i.e. assuming that $\sigma_p = 0$ [5]. To facilitate the reading of the figure, h_g, the hazard with a relatively good observation (i.e. $z_k > z^*$), is multiplied by 8.6, which is equal to $h_b(5)/h_g(5)$. We can see that the h_g begins to increase later than h_b, eventually catches up, and remains roughly proportional to h_b. The fact that h_g begins to increase later than h_b is explained by the fact that initially the prior belief has a strong influence on the woman's current belief. This means that she needs a really bad observation to separate. However, by definition h_g implies that she got a relatively good observation ($z > z*$), which is not sufficient to override the prior (and separation costs) and trigger separation. In Figure 3, we can see that the hazard ratio in the fixed match quality model decreases and then stabilizes as the relationship duration increases.

In panel B of Figure 2, I plot $h_b(k)$ and $h_g(k)$ under the mixed model, i.e. assuming that $\sigma_p > 0$ and $\sigma_{obs} > 0$. The hazards calculated in panel B use the same parameters as those calculated in panel A, except that $\sigma_p = 5$ instead of $\sigma_p = 0$. In this case like in the pure learning case, h_g begins to increase later than h_b and eventually catches up. However, past 5 periods, the two hazards are not proportional: instead, h_g decreases faster than h_b. To understand why this is the case, first note that h_g is driven by low quality relationships only, since only they are led to separate even in the absence of a bad observation. By contrast h_b is driven by both low quality relationships and mediocre relationships that end up separating due to a bad observation. Now, the proportion of low quality relationships decreases fairly steadily over time as more and more low quality relationships dissolve. However, the proportion of mediocre relationships decreases slower and slower over time: this is because while most relationships start out well above the separation threshold, some of them eventually randomly drift into the "'mediocre"' quality zone. When looking at the hazard ratio in Figure 3 for the mixed model with changing match quality, we see that it first decreases with relationship duration, and subsequently increases again. The

[5] Table 1 gives the specific parameters used. Note that constant separation costs are assumed.

initial decrease is due to learning ($\sigma_{obs} > 0$) while the subsequent increase is due to changes in relationship quality ($\sigma_p > 0$). Accordingly, by performing the same calculations with different values of σ_{obs}, one can see that the initial decrease in the hazard ratio is stronger with a higher σ_{obs}, i.e. when there is more scope for the woman to keep learning new things about the relationship as time goes by. Similarly, the subsequent increase in the hazard ratio is stronger as σ_p increases[6]. To be complete, note that under some parameters, we could observe an increasing and then decreasing hazard ratio even if $sigma_{obs} = 0$ (pure changes model), but the considerations in the next paragraph make it possible to distinguish between the mixed model and the pure changes model.

So far, we have examined the effect of observing a bad signal at length k on separation at length k. However, it is also interesting to ask how this effect evolves over time: relative to those relationships that did not get a bad signal at length k, how much more likely are relationships who did get a bad signal at length k to dissolve at lengths $k+1$, $k+2$, ..., $k+n$? If there is no learning, i.e. in the pure changes model, this question is uninteresting. Indeed, since the signal is a perfectly accurate reflection of true relationship quality, those relationships that get a bad signal at tenure k dissolve immediately if the signal is below the threshold. For the pure learning or the mixed model, one can answer this question by computing the hazard of separation at lengths $k+1$,..., $k+n$ separately for those relationships that did get a bad signal at k and those that did not. Figure 5 plots the ratio of these two hazards for $k = 5$ (the two hazards are the hazard if a bad signal was observed at length 5, and the hazard if no bad signal was observed at length 5) for both the pure learning model ($\sigma_p = 0$) and the mixed model ($\sigma_p = 5$). The figure shows that in both models the hazard ratio is largest in the periods immediately following period 5. Thereafter, we can see that in the pure learning model, the hazard for those relationships that got a bad observation at 5 remains larger than the hazard for those relationships that did not get a bad observation at 5 (the ratio is no lower than 2.2). By contrast, in

[6] An increase in σ_p increases both h_b and h_g. However, while the increase in h_b is roughly proportional at all relationship durations, h_g increases much more at low relationship durations. This is what drives the steeper increase in the hazard ratio h_b/h_g when σ_p increases.

the mixed model, the difference between the two hazards disappears with time (the ratio converges to 1). These qualitative conclusions do not depend on the choice of $k = 5$. The intuition for these results is as follows. In the pure learning model, the true quality of the relationship is fixed. As a result, relationships that got a bad observation at 5 are on average worse than those that did not, and this difference persists over time. For both those relationships that got a bad observation at 5 and the others, learning continues until hazards converge to zero; however, until then, there will be more separations among relationships that got a bad observation at 5 because they are worse on average. In the mixed model, relationship quality changes continuously. As in the pure learning model, those relationships that got a bad observation at 5 are on average worse than those that did not. However, since relationships evolve according to a random walk after length 5, their quality at length 5 is less and less informative about their present quality as time goes by, and after a while the two groups no longer differ in their separation hazards[7].

2.3 Summary of testable implications of the model

We can now summarize the testable implications of the model. In the empirical application, we are going to assume that a negative labor market shock is a bad signal of relationship match quality in the sense described above.

Implication 1. As long as separation costs are not too high and do not strongly decrease over the course of the relationship, the hazard of separation will converge to 0 as relationship duration increases in the case of a pure learning model, but not in the case of the pure changes or the mixed model[8].

Implication 2. Under both the pure learning model and the mixed model, the impact of a labor market shock on separation is positive and decreases with time elapsed since the shock. However, while under the pure learning model, the impact of labor market

[7]This also holds if the AR(1) process is stationary. Indeed, since all relationships converge to the long-run mean, past history becomes less and less relevant.

[8]In principle, it is possible that the hazard does converge to 0, but we do not observe relationships for long enough. Therefore, to use this implication, we have to assume that the window of observation is sufficiently long.

shocks remains positive, under the mixed model the impact of a labor market shock tends toward 0 as time passes after the shock.

Implication 3. The ratio between the hazard with a negative labor market shock and the hazard without such a negative labor market shock decreases and eventually stabilizes with relationship duration in the case of the pure learning model. In the case of a mixed model, the hazard ratio decreases and then increases with relationship duration.

3 Empirical Evidence: main results

3.1 Data used

I use monthly data from the Survey of Income and Program Participation 1990, 1991, 1992, 1993, 1996, and 2001. I retain all observations of persons who are either married or cohabiting as a couple[9]. The data is reshaped so that the panel identifier corresponds to relationships, not individuals. This entails that for individual characteristics, there is one variable for the woman and one for the man. In gay couples, the man is defined as the partner who is most often the head of household, and if there is a tie, the man is the partner who has the lowest ID number[10]. Relationships where none of the partners is ever observed to be the head of the household are not in the sample: indeed, these are special cases such as young couples living durably with their parents. Relationships are observed for at most 4 years, and the average window of observation for a relationship is 26 months or a bit more than 2 years. The starting date of left-censored relationships is only known for marriages, so I drop left-censored cohabitations. A relationship is defined to end the first time I observe a separation or a divorce. A relationship is right-censored whenever there is any gap in the observations for either partner, and that gap is not explained by separation or divorce. Labor market shocks include getting laid off, fired,

[9] Cohabiting couples are identified with noise before 1996, since the variable for "'relationship to head"' only includes a category "'partner/roommate"', without any further break-down. However, the main results in this paper are robust to excluding cohabiting couples before 1996, as discussed in section 4.

[10] I drop relationships if any partner changes gender, or if there is more than one partner of the head.

or becoming disabled. For each category, I retain only the first such event observed in the sample. This is to insure a better consistency with the model: indeed, the model assumes that relationships have "normal" histories before the shock and so using second shocks would make this assumption less plausible. Laid off and fired are two possible responses to the question of why the last job ended; the distinction is therefore based on self-reports. Someone experiences a job loss when they were either laid off or fired. Disability is defined as any condition that limits the amount or type of work a person can do.

Table 1 reports summary statistics for the variables of interest. The monthly probability that a relationship ends in separation or divorce is 0.26%, which amounts to 3.1% per year. There are 95409 relationships in the sample, and of those 6.9% end during the observation period. The large majority of relationships in the sample are marriages: marriages make 93.8% of the observations. Labor market shocks are fairly uncommon: for example, the probability that in any given month the man has been fired during the past year is 0.29%. Thus, one really does need a large sample to investigate the impact of labor market shocks on relationship dissolution, especially since we want to allow this impact to vary with the duration of the relationship. Also, since labor market shocks in any given month are so rare, it was necessary to define labor market shocks over the past year to get a measure that is not too noisy. Moreover, we can reasonably hypothesize that, due to transaction costs and delays, it takes at least a few months for a relationship to be dissolved once it's been hit by a fatal negative shock; this justifies looking at labor market shocks that occured longer ago than the current month or one or two months earlier.

3.2 Econometric specification

Basic specifications will use a Cox proportional hazard model. Such a model assumes that the hazard of separation at relationship length k is given by:

$$\lambda(k; X) = \lambda_0(k) exp(\beta' X) \tag{16}$$

where $\lambda_0(k)$ is the baseline hazard estimated non parametrically, and X is the set of covariates we are interested in. The Cox model assumes that these covariates have a proportional effect on the baseline hazards.

Since we are also interested in how the impact of labor market shocks varies with relationship duration, we want to relax the proportionality assumption by allowing the coefficient β to be time-varying. Assume the hazard is given by:

$$\lambda(k; X) = \lambda_0(k) exp[\beta' + m(k)' X] \tag{17}$$

If we assume that $m(k) = 0$, i.e. that the standard Cox model is correct, then the maximum likelihood estimate of β, $\hat{\beta}$, satisfies:

$$\sum_{i \in D} \left\{ X_i - \frac{\sum_{j \in R_i} X_j exp(X_j' \hat{\beta})}{\sum_{j \in R_i} exp(X_j' \hat{\beta})} \right\} = 0 \tag{18}$$

where D is the set of indices for those relationships that end and R_i is the set of relationships that are at risk when relationship i ends. Schoenfeld's (1982) residuals are defined as:

$$\hat{r}_i = X_i - \frac{\sum_{j \in R_i} X_j exp(X_j' \hat{\beta})}{\sum_{j \in R_i} exp(X_j' \hat{\beta})} \tag{19}$$

Grambsch and Therneau (1994) showed that $E(\hat{r}_i) \approx V_i g(k_i)$, where V_i is the variance matrix of β, and k_i is the time when relationship i ends. Thus a smoothed plot of $\hat{V}_i^{-1} \hat{r}_i + \hat{\beta}$ versus relationship duration k will reveal the functional form of $\beta(k)$.

Finally, note that the sample of left-censored marriages is a stock sample with follow-up. Therefore, I use the enter option in Stata's stcox command to specify that these marriages only enter the sample at the date of the first interview, and are therefore only at risk of dissolution after that date.

3.3 Results

Figure 5 plots the non-parametric estimate of the separation hazard, allowing for a different hazard in those cases where the man or the woman experienced a labor market shock (was laid off, fired, or became disabled) for the first time during the last year. Beside its descriptive interest, Figure 5 allows us to use Implication 1 from the theory. Descriptively, we notice that the hazard in the presence of a labor market shock is significantly higher than in the absence of such a labor market shock. The difference between the two hazards is substantial, especially in the first 8 years or so, where those relationships that experiences a labor market shock seem to be roughly twice as likely to end than the others. Both hazards initially increase with relationship duration and eventually decrease. Moreover, notice that both hazards are significantly larger than 0, even after 20 years of marriage[11](240 months). Using Implication 1, this strongly suggests that changes in relationship quality are needed to explain the pattern of the separation hazard, and makes us reject the pure learning model. Indeed, since the hazard does not converge to 0 even after 20 years, it is hard to believe that we don't observe these relationships for long enough to see the hazard converge to 0; after 20 years, people should have learned what there was to learn about any time-invariant components of their relationship. Using Implication 1 is also subject to the caveat that strongly decreasing separation costs could lead to a non-vanishing separation hazard even in the pure learning model. However, it does not seem very likely that separation costs strongly decrease over the course of a marriage: by and large, the longer couples have been together, the more they have invested in the relationship, and moreover as people age the costs of finding a new partner tend to

[11]Since left-censored cohabitations are dropped and relationships in the sample are observed for at most 4 years, 20 years long relationships have to be marriages.

increase. It is therefore reasonable to conclude from the shape of the separation hazards in Figure 6 that changes in relationship quality play an important role in explaining the dissolution of relationships.

Table 3 estimates the impact of various labor market shocks on the separation hazard, assuming that this impact does not vary with relationship duration. In column 1, we see that the man or the woman getting laid off, fired or becoming disabled all significantly increase the probability of relationship dissolution. The effects do not differ significantly between men and women, and the largest impact is from either the man or the woman getting fired. In column 2, I add the wage and labor force participation controls for both men and women: average earnings for the past 12 months, number of months unemployed in the last 12 months, and number of months inactive in the last 12 months. This allows me to control for the immediate economic impact of labor market shocks, and so we expect the impact of these labor market shocks to be lesser once these factors are accounted for. Indeed, all coefficients drop from column 1 to column2. The relative drop in the point estimate is largest for layoffs, which suggests that among the three shocks considered, layoffs are those whose impact on relationship dissolution is best accounted for by immediate economic consequences.

In column 3, I use a different set of controls that do not measure the immediate economic impact of labor market shocks but characteristics that may otherwise affect the probability of relationship dissolution. Some of these controls do not pass the proportional hazard test (Stata's stphtest uses the Schoenfeld residuals), and they are therefore either stratified on or interacted with a function of relationship duration[12]. The controls that are stratified on are : house ownership dummy, a dummy taking the value 1 if only one of the partners is a high school dropout or if both partners are high school graduates, a dummy taking the value 1 if one of the partners is a high school graduate and the

[12]Using the model without stratifying or interacting any control with a function of relationship duration does not qualitatively affect any of the main results. In Stata, one cannot stratify on more than five variables, and I therefore decided to stratify on those that most significantly failed the proportional hazard test, and interact the remaining variables with a quadratic in relationship duration

other has some college education, a dummy taking the value 1 if both partners have some college education[13], and a dummy taking the value 1 if a married couple ever cohabited. The other controls included are: the number of couple's own kids under 18 interacted with a quadratic in relationship duration, whether there are other kids in the household besides the couple's own, married dummy, age at the beginning of the relationship, age difference between the partners (set of dummies: woman older by 5 years or more, man older by 5 years or more), white man dummy, same race dummy, and an interaction of a dummy for people who live together but never marry and a dummy for the survey year being before 1996. All individual level controls are included separately for men and women. The inclusion of these other controls makes all coefficients drop compared to column 1. The relative drop is generally larger than the drop in coefficients resulting from adding wage and labor force participation controls in column 2. Once again, the relative drop is largest for the coefficient on "'first laid off last year"', at least within gender. However, for men, the drop in the coefficient on "'fired last year is almost as large as on "'first laid off last year"'. In other terms, these controls tend to account best for the impact of lay offs, but they account almost as well for the impact of getting fired.

In column 4 of Table 3, controls from column 2 and 3 are added together. Compared to column 1, coefficient on layoff diminishes most in relative terms, so that it becomes barely significant for men and totally insignificant for women. Getting fired has the largest impact on the probability of relationship dissolution: +38.5% if the man got fired and +30.8% if the woman got fired. Becoming disabled also has a significant impact on the probability of a separation or divorce: +24.2% if the man experiences this shock and +29.3% if the woman does.

The fact that getting fired has the largest impact on the probability of relationship dissolution, even after accounting for its economic impact, may be attributed to the fact that such a shock is most likely to indicate that the partner who experienced it has bad

[13]These education dummies were chosen after examining the coefficients in the unstratified model on all combinations of the three education categories.

character. Indeed, why is it that their boss fired them in the first place? Presumably their conduct on the job was less than satisfactory. One can hypothesize that behavior on the job and behavior in the relationship are correlated, which explains why getting fired has an important effect on relationship survival. On the other hand, a layoff is more indicative of the firms' circumstances than of the character of the person who has been laid off. A layoff still signals reduced economic opportunities in the future, and so it can still have an effect on relationships in as much as partners care about their economic well being. Moreover, reduced economic opportunities can lead to strains on the relationship. The effect of disability on relationship duration is least affected by the addition of controls. This may be an indication that the impact of the disability on the functioning of the relationship is fairly direct rather than mediated by other factors: e.g. for example a disabled partner may not be able to engage in certain types of leisure activities, etc.

Table 4 analyzes how sensitive the results are to the definition of the period over which a labor market shock occurred in the past, and allows us to us Implication 2 from the model. Focusing on column 4 with the full set of controls, we see that the impact of the man getting fired on separation *today* is only significant if that event happened 1 to 6 months ago, and not if the event happened happened a longer time ago. The same pattern applies to the man becoming disabled. The impact of the man getting laid off on separation *today* is largest if the layoff happened 7-12 months ago[14] Since a layoff seems to be less negative an event than the two other types of labor market shocks considered, it may be that, given the costs incurred in the process of separation, the wife prefers to wait a little before separating. Overall, these results indicate that, first, examining the impact of a job loss happening during the last year is a reasonable choice. Second, using Implication 2, we can say that the results support the mixed model against the

[14]For women, the results are muddier. The coefficients in the specification from column 4 are insignificant for getting laid off (except for a 10% level significance for getting laid off 19-24 months ago, but the sign of the coefficient is negative) or fired. For becoming disabled, all coefficients but the one on becoming disabled 19-24 months ago are insignificant.

pure learning model, since the impact of labor market shocks becomes insignificantly different from 0 with time elapsed since the shock. However, the standard errors for shocks occurring more than a year ago are large, so the results do not strongly reject the pure learning model.

Figure 6 plots the non-parametric estimate (scaled Schoenfeld residuals smoothed using the lowess command in Stata, with a bandwidth parameter of 0.5) of the impact of labor market shocks on relationship dissolution as a function of relationship duration, and thus allows us to use Implication 3 from the theoretical model. Generally, the pattern is such that the impact of labor market shocks initially diminishes with relationship duration, increases strongly thereafter, and eventually decreases. Even in the case of the man or the woman getting fired, the impact eventually decreases with relationship duration, but the decrease occurs later and is therefore not captured in the graph. The variation in the impact of labor market shocks with relationship duration is quantitatively very large: typically, the impact is close to 0 at its minimum and reaches between about 40% higher chance of relationship dissolution to twice as large a probabiility of relationship dissolution. The maximum effect is largest for the man getting fired, consistent with the point estimates in Table 3. It is also important to notice that the largest impacts are much larger than the point estimates in Table 3, column 4, and especially so for the man getting laid off or fired, and for the woman getting fired. This means that assuming that the impact of these labor market shocks is constant with reltionship duration misses a very important heterogeneity. The pattern observed in these figures is consistent with the theoretical predictions for the mixed model illustrated in Figure 4, and therefore allows us, using Implication 3, to reject the pure learning model. However, the evidence is consistent with some learning since the impact of the man's getting fired first decreases with relationship duration: this allows us to reject the pure changes model. One might ask why the impact of the impact of labor market shocks finally diminishes with relationship duration, contrary to theoretical predictions. First, note that because overall the hazard of separation tends to decrease with relationship duration after 5 years (see Figure 5), there are fewer and fewer observations where a relationship ends *and* a labor market shock occured, which means that estimates become imprecise. On the other hand, while the model does not predict a decrease in the impact of a bad observation at high relationship duration, we have noted earlier that it does a bad job at explaining relationships where partners are older. This is because the model assumes that one can always get a new partner in case of separation AND that one will have a substantial time to enjoy this new relationship, both of which are less likely to be true when people are older. Since older relationships involve on average older people, the predictions of the model may not hold for them.

The reason why the impact of the man's getting fired increases with relationship duration past the first two years (and up to 12 years) is most likely that over time there are more and more relationships whose quality is fairly mediocre (rather than really bad), and so this increases the proportion of relationships that are at risk of dissolving if they are hit by a bad shock relative to those relationships who are at risk of dissolving even in the absence of a shock. The psychology literature seems to confirm this hypothesis. Indeed, using longitudinal data, Kurdek (2005) shows that marital satisfaction decreases in the first years of marriage, especially for women. Moreover negative attributions (i.e. good husband behavior is due to external causes and bad behavior is husband's responsibility) increase in the first years of marriage, especially for women (Karney and Bradbury, 2000). This implies that the longer the duration of the relationship, the more likely the wife is to make the husband responsible for his losing his job.

It would be important to confirm these findings in the present study. However, the SIPP does not provide any direct information on marital satisfaction. For this reason, I turn to another data set to investigate the plausibility of this hypothesis. The National Survey of Families and Households contains such information. The overall sample for the first wave conducted in 1987-1988 includes a main representative cross-section of 9,637 American households plus an oversampling of blacks, Puerto Ricans, Mexican Americans, single-parent families, families with step-children, cohabiting couples and recently married persons. The survey asks married people about the date of their marriage, so I can reconstruct their relationship duration as of the date of the interview. The survey also asks questions about marital happiness on a 1-7 scale and the subjective probability of divorce on a 1-5 scale. The latter would seem to best correspond to the theme of this study. However, the subjective probability of divorce has fewer possible values and is much more skewed than marital happiness. For these reasons, I choose to focus on marital happiness. Marital happiness is indeed negatively correlated (-0.48) with the subjective probability of divorce. For example, among women with level 5 of satisfaction, only 50% rate their probability of divorce as very low, vs. 72% at level 6 and 91% at level 7. In Figure 7, I plot the distribution of women's responses to the question about marital happiness as a function of the duration of their relationship. I find that women who have been married for less than 6 months are most likely to report being "very happy" with their marriage. The proportion of those who declare themselves very happy decreases quite strongly with relationship duration, and this decrease is faster earlier in the relationship. A parallel phenomenon is that the proportion of those who declare themselves only "somewhat happy" (category 5) increases quite dramatically with relationship duration. On the other hand, the proportion of those who declare themselves unhappy to any degree does not change over time. This evolution in the distribution of marital bliss can explain why the impact of a husband's getting fired increases with time: indeed, in older relationships, wives are less likely to be satisfied and therefore a negative labor market outcome affecting their husband is more likely to trip the marriage. Finally, note that the way marital happiness evolves in cross-sections of marriages of different durations is not consistent with what one would expect based on the pure learning model: indeed, in the pure learning model we would expect to see more relatively unhappy wives at short marriage duration than at long marriage duration. Under the learning model, people wait until they have enough information and only then separate, which means that in the beginning we should see more unhappy wives because they are not yet sure whether they should separate. The pattern in Figure 9 is rather consistent with a model where relationships evolve over time, and tend to regress to the mean (this could be modeled by assuming $\rho < 1$ and $c > 0$ in equation (1)). The evidence in Figure 7 does not preclude that wives are somewhat uncertain about the quality of their relationship, but it is inconsistent with the pure learning model.

4 Further empirical results and robustness tests

One first concern with the results presented in the previous section is that they may be driven by cohabiting people, or even by roommates since before the 1996 SIPP survey, it is not possible to distinguish cohabiting partners from roommates. To check for the sensitivity of the results to these concerns, I first dropped any cohabiting couples, and reset the date of the beginning of the relationship to be the date of the beginning of marriage, even for those couples who were seen cohabiting in the sample. The results in Table 3 are broadly unaffected by this change, the only exception being that the impact of the man's getting laid off increases in magnitude and significance, even when all controls are included. However, this sample restriction has some impact on the results presented in Figure 6. One can indeed expect that if we exclude cohabiting people, we see fewer relationships that are at early stages and so we are less likely to see the initial decrease in the impact of labor market shocks due to learning. And indeed, this is what happens as we no longer see much of these early decreases in the impact of labor market shocks. Still, decreases can be seen for some of the labor market shocks, such as the man getting fired. However, we still see the impact of labor market shocks goes up with tenure. Second, I dropped all cohabiting couples who were sampled in surveys prior to SIPP 1996 and never married. This allows us to drop all potential roommates. The results do not substantially change in any respect with this sample restriction, which was largely to be expected since a dummy for these potential roommates was already included in the main analysis.

A second concern is that the initial decrease in the impact of labor market shocks on relationship dissolution illustrated by Figure 6 may be due to a sample selection issue.

Indeed, in the main analysis, variables of the type "‘first labor market shock occurred in the last year"’ were not missing for those cases where the relationship was observed for less than one year prior to the shock considered. This raises the possibility that during the first 12 months, as relationship duration increases, we have a larger and larger proportion of relationships that have not been dissolved even though a shock occurred, and the increasing representation of such better relationships would naturally decrease the measured impact of labor market shocks. To investigate this issue, I set variables of the type "‘first labor market shock occurred in the last year"’ to missing when the relationship was observed for less than one year prior to the shock considered. This change does affect the results in Figure 6 in a predictable fashion, since the impact of labor market shocks occurring in relationships younger than 12 months can no longer be measured. However, we still observe an initial decrease in the impact of labor market shocks (except possibly in the case of the woman getting fired).

Finally, one may wonder whether there is any significant interaction effect between the labor market shocks considered and other relevant variables. First, I checked whether the impact of labor market shocks varied by race and found no significant interaction effect. Second, I checked whether the impact of labor market shock varies with the education level of the person who experiences the shock (in this case, I did not stratify by education but included educational dummies as controls). I found that if anything, college educated individuals are more adversely affected than high school graduates or high school dropouts: in particular, getting fired or becoming disabled has a significantly larger effect on the probability of separation if the affected man has some college education, while college educated women are significantly more likely to experience a relationship separation after getting laid off. One possible explanation of these results is that college educated individuals are most likely partnered with other college educated individuals, and college educated partners have better outside options, either because their higher income allows them to live comfortably even if single, or because they find it easier to get a new mate. Third, I investigated whether there is any interaction effect between the state average unemployment rate during the last year and labor market shocks. Indeed, one could expect that a labor market shock is less of a bad signal about a person if unemployment is higher. I thus included both the unemployment rate and interactions with each of the labor market shocks considered. While the unemployment rate came out positive and significant, suggesting that higher unemployment rates increase relationship dissolution, the interactions were generally not significant. As expected, interactions were generally negative for both lay offs and discharges, however the interaction was only significant for the woman getting laid off.

5 Conclusion

This paper has shown that couples who have been together for longer are not necessarily less likely to separate in the face of an adverse labor market shock. In particular, considering the first ten years of a relationship, if the man in the couple gets fired, then, past the first two years of the relationship, the longer the relationship the higher the risk of separation. This evidence is not consistent with a pure learning model where people are uncertain about the quality of their relationship but learn about it over time. Instead, the evidence supports a mixed model with both some uncertainty about relationship quality and some mean-reverting changes in relationship quality. Further, the analysis shows that, once we account for a large number of controls, layoffs have a relatively limited impact on relationship dissolution, while discharges for cause and the onset of disability have a strong and significant impact. This suggests that adverse labor market shocks, beyond their economic impact, have a negative effect on couples' stability which should be accounted for when analyzing the welfare impact of such shocks.

References

[1] Arulampalam S., Maskell S.,Gordon N., Clapp T. (2002), "A Tutorial on Particle Filters for Online Nonlinear/Non-Gaussian Bayesian Tracking", *IEEE Transactions on signal processing*, Vol. 50, No. 2, Feb. 2002.

[2] Cassandra A. R. (1998), "Exact and Approximate Algorithms for Partially Observable Markov Decision Processes", Ph.D. thesis, Brown University, May 1998.

[3] Charles K. and Stephens M. "Job Displacement, Disability, and Divorce", *Journal of Labor Economics*, April 2004, vol.22, n.2, p.489-522.

[4] Conger, R.D., Rueter, M.A., Elder, G.H. Jr, *Journal of Personality and Social Psychology*, 1999 Jan, 76(1),54-71.

[5] Farber H. S. (1994), "The Analysis of Interfirm Worker Mobility", *Journal of Labor Economics*, Vol 12., 554-593.

[6] Gibbons R., Katz L., "Layoffs and Lemons", *Journal of Labor Economics*, 1991, vol. 9, no. 4, 351-380.

[7] Grambsch P., Therneau T., "Proportional Hazards Tests and Diagnostics Based on Weighted Residuals", *Biometrika*, Vol. 81, No. 3. (Aug., 1994), pp. 515-526.

[8] Hauskrecht M. (2000), "Value-Function Approximations for Partially Observable Markov Decision Processes", *Journal of Artificial Intelligence Research*, 13 (2000) 33-94.

[9] Hitsch G., Hortacsu A., Ariely D., "What Makes You Click? Mate Preferences and Matching Outcomes in Online Dating", MIT Sloan Research Paper No. 4603-06, February 2006.

[10] Jovanovic B. (1979), "Job Matching and the Theory of Turnover", *The Journal of Political Economy*, Vol 87., 972-990.

[11] Kalmijn M., Poortman A., "His or Her Divorce? The Gendered Nature of Divorce and its Determinants", *European Sociological Review* Vol. 22, No. 2, April 2006, 201214.

[12] Karney B., Bradbury T., "Attributions in Marriage: State or Trait? A Growth Curve Analysis", *Journal of Personality and Social Psychology*, 2000, Vol, 78, No. 2, 295-309.

[13] Kinnunen U., Feldt T., "Economic stress and marital adjustment among couples: analyses at the dyadic level", *European Journal of Social Psychology*, 34, 519532 (2004).

[14] Kurdek L., "Gender and Marital Satisfaction Early in Marriage: A Growth Curve Approach", *Journal of Marriage and Family*, 67 (February 2005): 6884.

[15] Marinescu I. E.(2006a), "Shortening the Tenure Clock: The Impact of Strengthened U.K. Job Security Legislation", working paper, 2006.

[16] Mortensen D., Pissarides C., "Job Creation and Job Destruction in the Theory of Unemployment" , *Review of Economic Studies* 61 (July 1994) 397-415.

[17] Schoenfeld D., "Partial residuals for the proportional hazards regression model", *Biometrika*, 1982, 69, 1, p.239-241.

[18] Sullivan D., von Wachter T., "Mortality, mass-layoffs, and career outcomes: an analysis using administrative data", Federal Reserve Bank of Chicago Working Paper Series WP-06-21, 2006.

[19] Svarer M. (2004), "Is Your Love in Vain? Another Look at Premarital Cohabitation and Divorce", *Journal of Human Resources* 39(2), 523-536.

[20] Teulings C. N., Van Der Ende, M. A. (2001), "A Structural Model of Tenure and Specific Investments", CESifo Working Paper No. 532, August 2001.

[21] Weiss Y., Willis R. J. (1997), "Match Quality, New Information, and Marital Dissolution", *Journal of Labor Economics*, Vol. 15, No. 1, Part 2: Essays in Honor of Yoram Ben-Porath. (Jan., 1997), pp. S293-S329.

Figure 1: Timing of partner's decisions

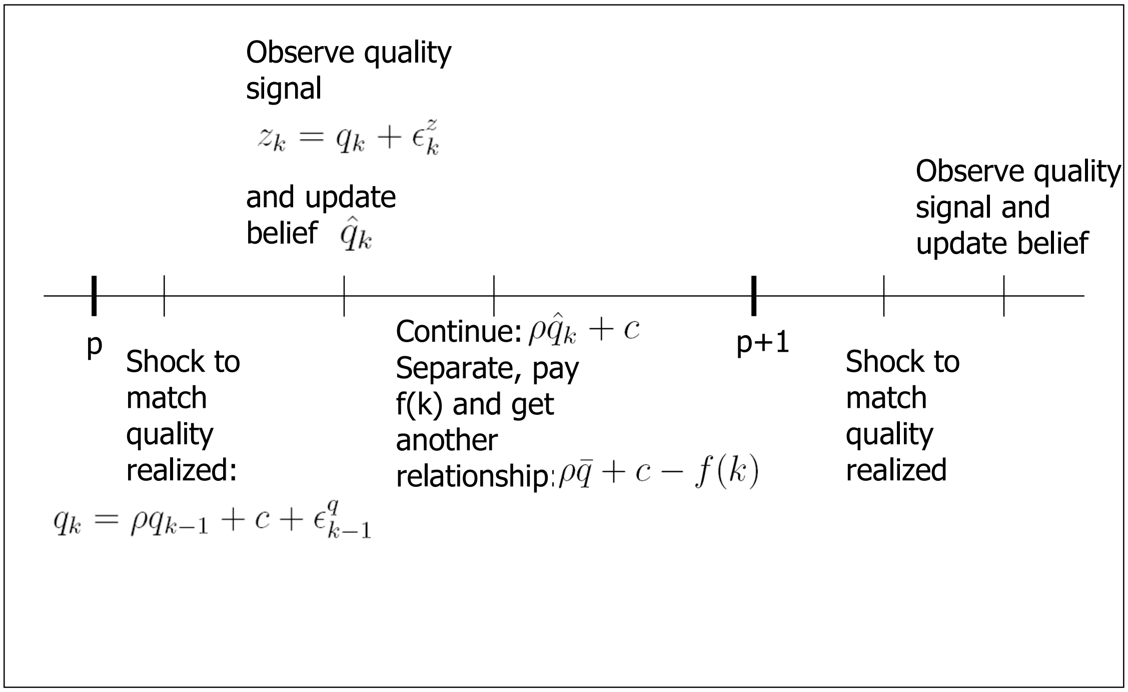
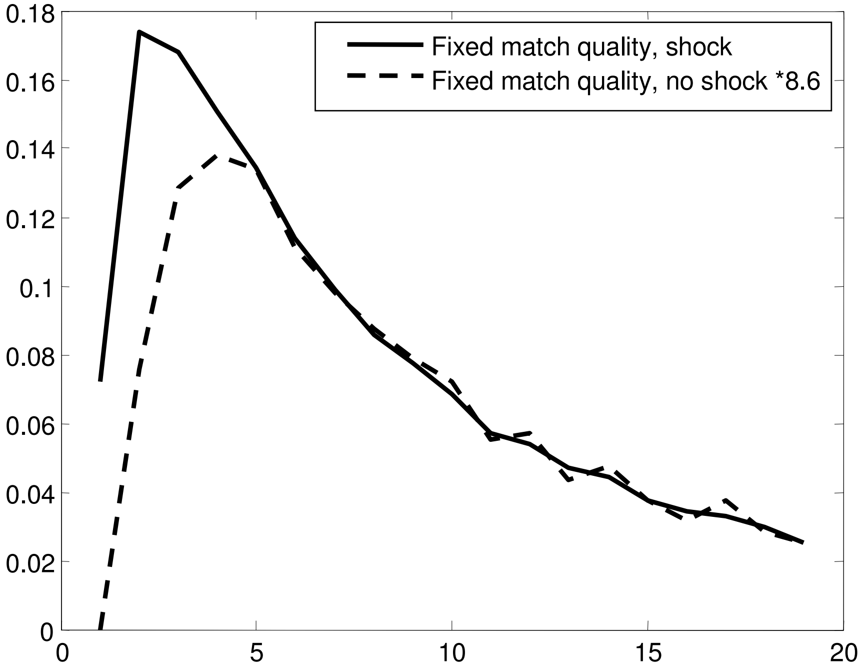


Table 1: Model parameters

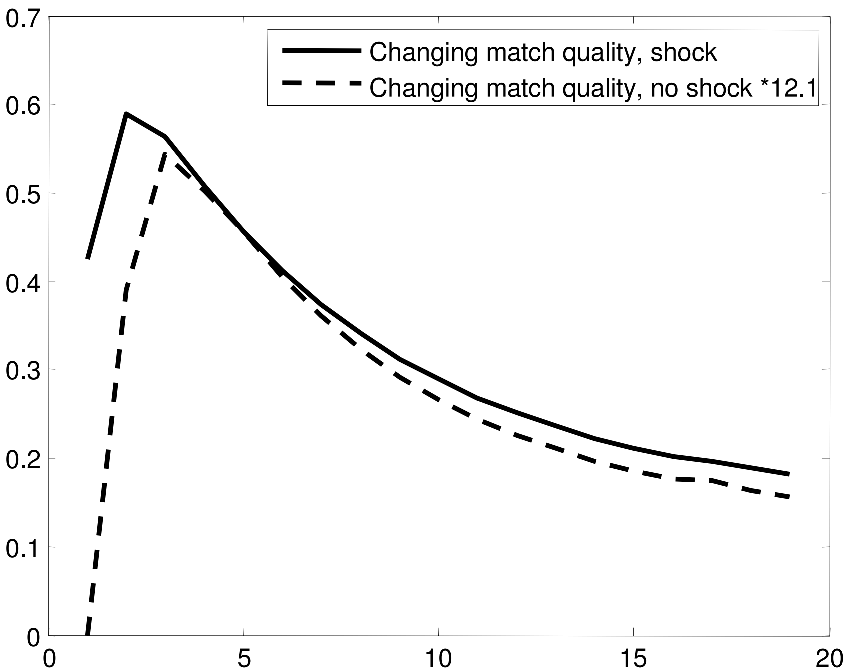
	Fixed match quality	Time-varying match quality
Parameters of interest		
Mean of prior	30	30
Standard deviation of prior	5	5
Standard deviation of process	***0***	***5***
Drift of process	0	0
Auto-correlation of process	1	1
Standard deviation of observation	10	10
Threshold for bad observation	10	10
Separation cost	30	30
Discount factor	0.85	0.85
Technical parameters		
Range of match qualities	[0,60]	[0,60]
Number of match quality values	801	801
Maximal length	50	50

Figure 2: Hazards with fixed and changing match quality

Panel A

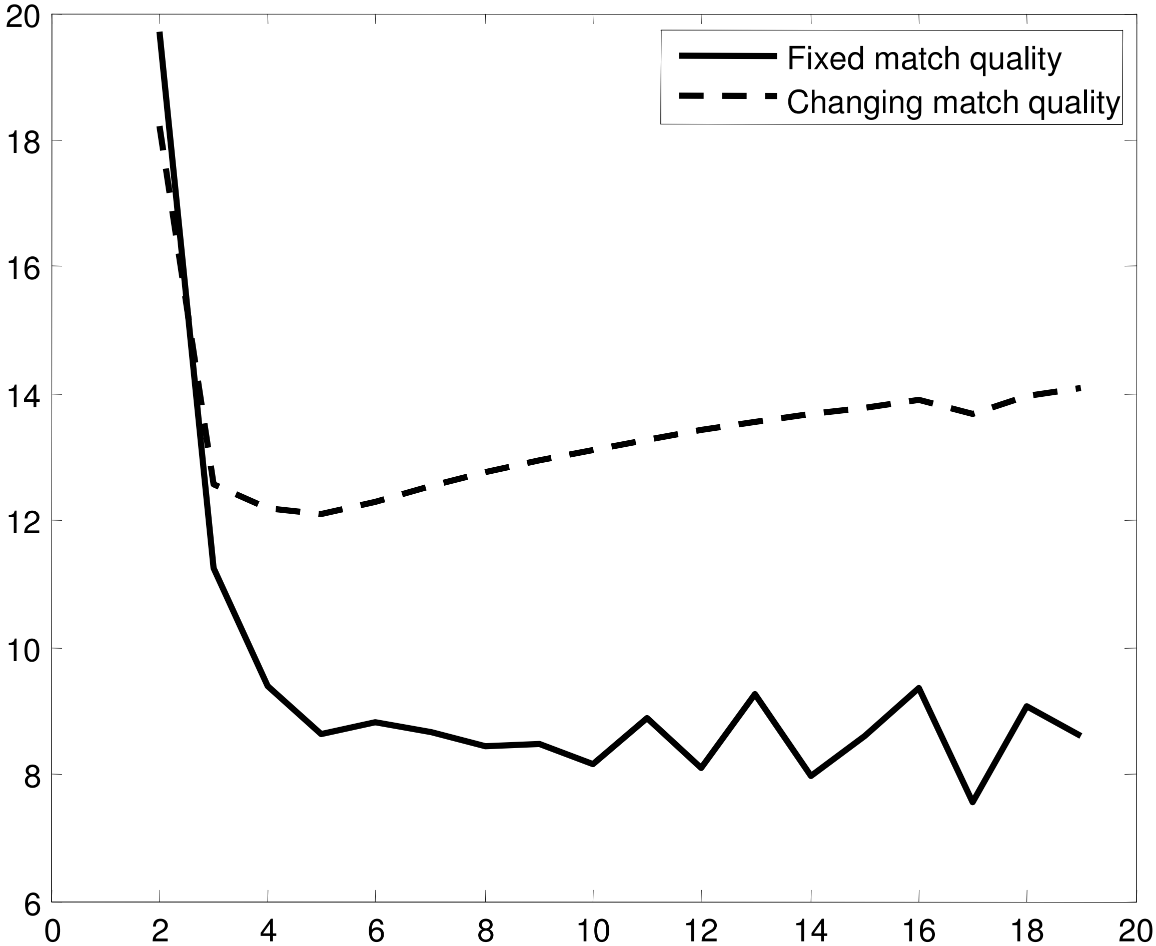


Panel B



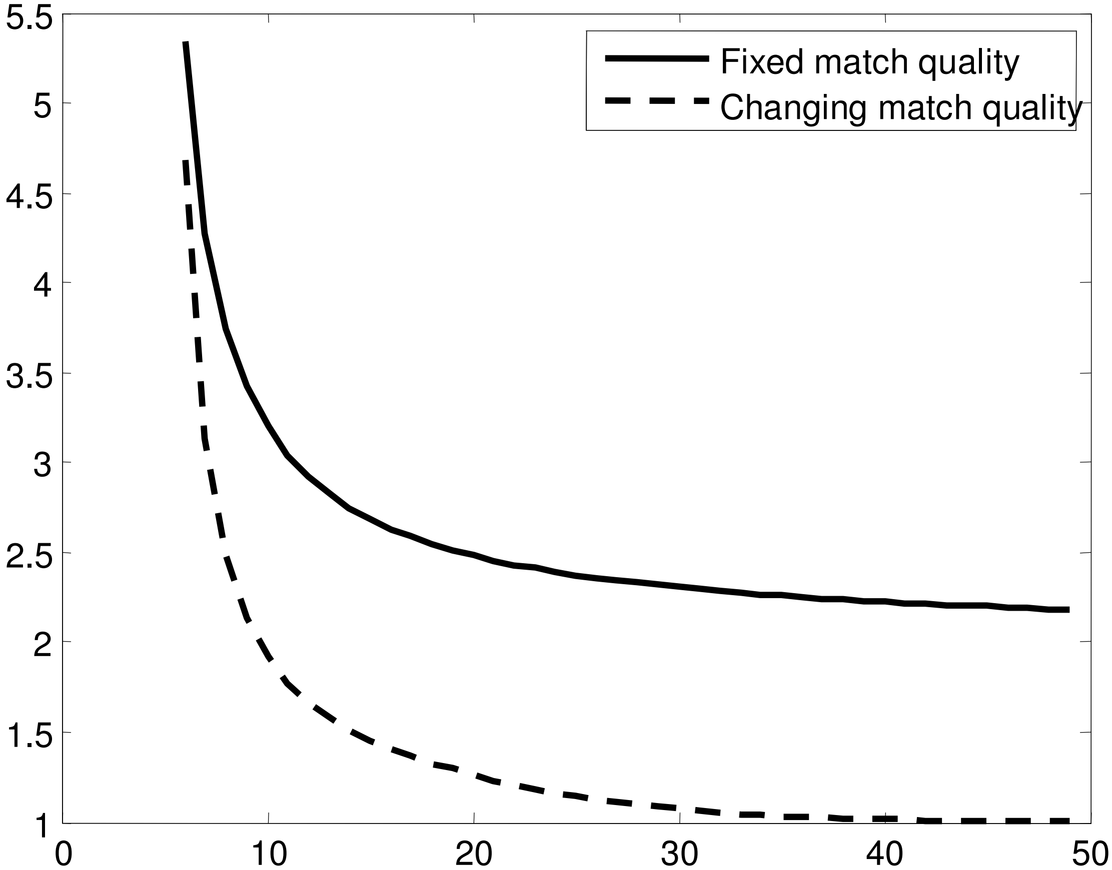
Note: The parameters for the calculation of these hazards can be found in Table 1.

Figure 3: Hazard ratios



Note: The parameters for the calculation of these hazards can be found in Table 1. By hazard ratio, it is meant "hazard if labor market shock occurred at k"/"hazard if no labor market shock occurred at k". k is represented on the x axis.

Figure 4: Hazard ratios after a shock occurred at period 5



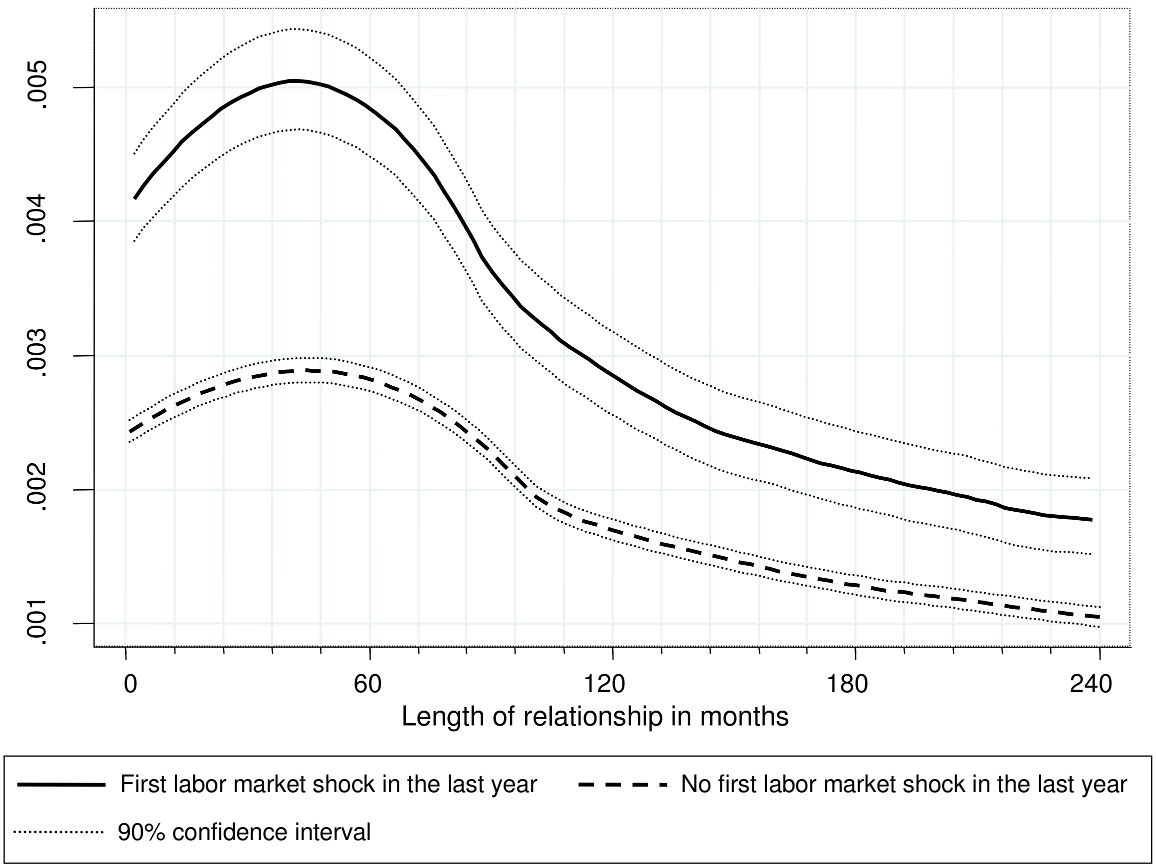
Note: The parameters for the calculation of these hazards can be found in Table 1. By hazard ratio, it is meant “hazard at k if labor market shock occurred at 5”/”hazard at k if no labor market shock occurred at 5”. k is represented on the x axis.

Table 2: Summary statistics for variables of interest

	Observation level			Relationship level		
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.
Relationship ends	2522893	0.0026	0.0510	95409	0.0685	0.2526
Married	2522893	0.9383	0.2406	95409	0.9022	0.2970
Man first laid off in the last year	2522893	0.0129	0.1130	95409	0.0342	0.1818
Woman first laid off in the last year	2522893	0.0090	0.0944	95409	0.0241	0.1534
Man first fired in the last year	2522893	0.0029	0.0540	95409	0.0081	0.0898
Woman first fired in the last year	2522893	0.0021	0.0460	95409	0.0059	0.0769
Man first became disabled in the last year	2522893	0.0555	0.2289	95409	0.1430	0.3501
Woman first became disabled in the last year	2522893	0.0532	0.2245	95409	0.1377	0.3446

Source: Survey of Income and Program Participation, 1990, 1991, 1992, 1993, 1996, 2001.

Figure 5: Relationship separation hazard and labor market shocks



Notes: The dummy variable "First labor market shock in the last year" takes the value 1 if the woman or the man is fired, laid off or becomes disabled for the first time during the previous year. Each subdivision on the x axis corresponds to a year.
Source: Survey of Income and Program Participation, 1990, 1991, 1992, 1993, 1996, 2001.

Table 3: Impact of various labor market shocks on the separation hazard

	(1)	(2)	(3)	(4)
	No controls	Wage and labor force participation controls	Other controls	All controls
Man				
First laid off in the last year	0.494	0.319	0.260	0.178
	(0.098)***	(0.099)***	(0.099)***	(0.100)*
First fired in the last year	0.843	0.661	0.450	0.385
	(0.154)***	(0.154)***	(0.156)***	(0.157)**
First became disabled	0.323	0.258	0.262	0.242
in the last year	(0.060)***	(0.061)***	(0.062)***	(0.062)***
Woman				
First laid off in the last year	0.397	0.242	0.137	0.031
	(0.123)***	(0.124)*	(0.123)	(0.124)
First fired in the last year	0.863	0.695	0.405	0.308
	(0.168)***	(0.169)***	(0.169)**	(0.170)*
First became disabled	0.379	0.375	0.249	0.293
in the last year	(0.061)***	(0.062)***	(0.062)***	(0.062)***
Observations	2278963	2278963	2277258	2277258

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Notes: Cox proportional hazard model for the relationship ending in a separation or divorce. Last year means 1 to 12 months ago. Wage and labor force participation controls are: average earnings for the past 12 months, number of months unemployed in the last 12 months, and number of months inactive in the last 12 months. Columns 3 and 4 use a stratified Cox model. The controls that are stratified on are: house ownership dummy, a dummy taking the value 1 if only one of the partners is a high school dropout or if both partners are high school graduates, a dummy taking the value 1 if one of the partners is a high school graduate and the other has some college education, a dummy taking the value 1 if both partners have some college education, and a dummy taking the value 1 if a married couple ever cohabited. The other controls in column 3 are: number of couple's own kids under 18 interacted with a quadratic in relationship duration, whether there are other kids in the household besides the couple's own, married dummy, age at the beginning of the relationship, age difference between the partners (set of dummies: woman older by 5 years or more, man older by 5 years or more), white man dummy, same race dummy, and an interaction of a dummy for people who live together but never marry and a dummy for the survey year being before 1996. All individual-specific controls are separated into woman's and man's. Column 4 includes the controls from column 2 and 3.
Source: Survey of Income and Program Participation, 1990, 1991, 1992, 1993, 1996, 2001.

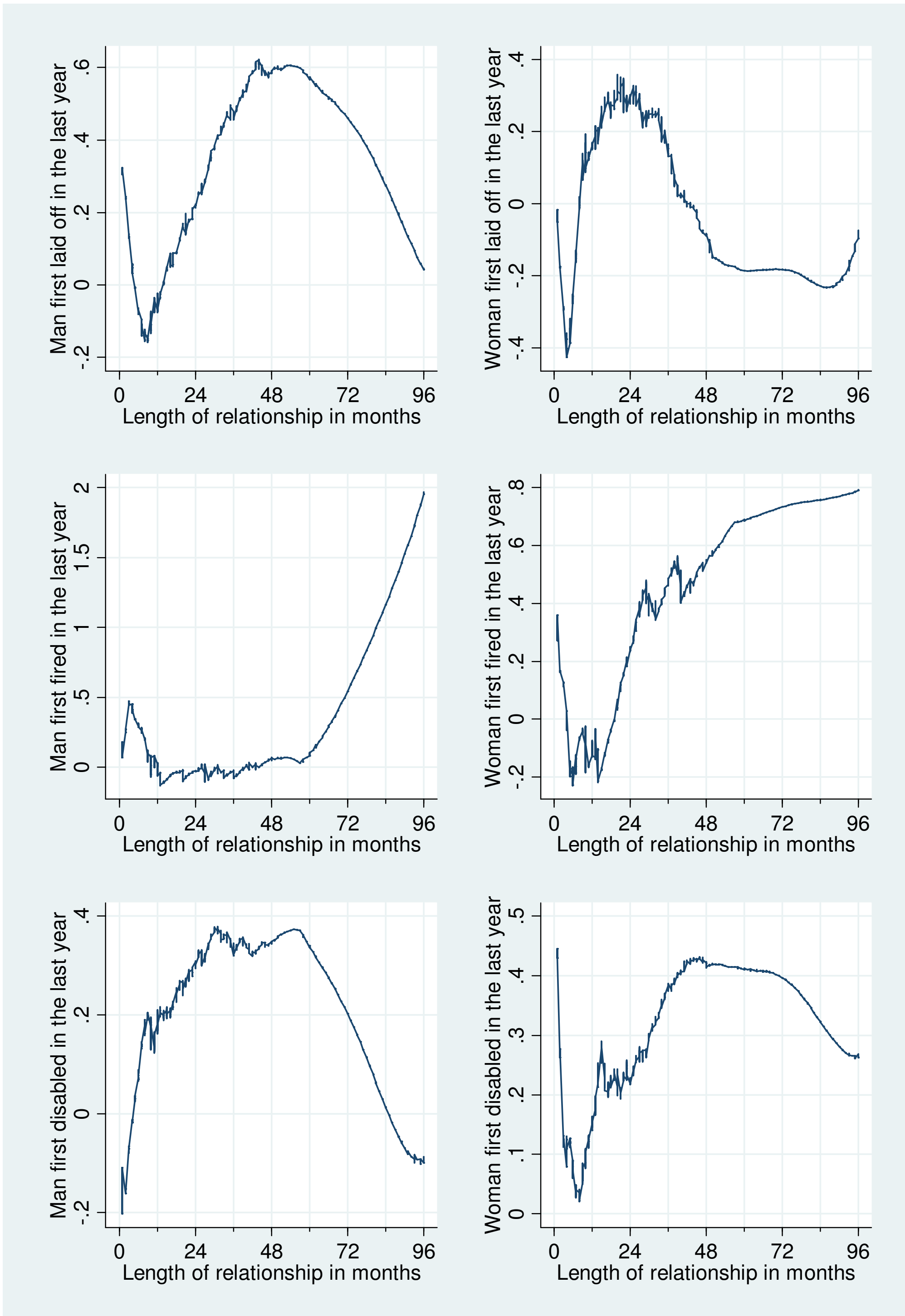
Table 4: Timing of the impact of labor market shocks

	(1)	(2)	(3)	(4)
	No controls	labor force participation controls	Other controls	All controls
Man				
First laid off 1-6 months ago	0.209	0.149	0.139	0.128
	(0.356)	(0.358)	(0.358)	(0.359)
First laid off 7-12 months ago	0.713	0.624	0.540	0.549
	(0.262)***	(0.270)**	(0.264)**	(0.274)**
First laid off 13-18 months ago	-0.019	-0.117	-0.341	-0.336
	(0.356)	(0.363)	(0.382)	(0.388)
First laid off 19-24 months ago	0.118	0.033	0.016	0.009
	(0.336)	(0.338)	(0.338)	(0.341)
First fired 1-6 months ago	1.270	1.219	1.008	0.994
	(0.382)***	(0.383)***	(0.418)**	(0.419)**
First fired 7-12 months ago	0.593	0.502	0.415	0.397
	(0.504)	(0.507)	(0.509)	(0.512)
First fired 13-18 months ago	0.264	0.147	0.071	0.027
	(0.580)	(0.584)	(0.583)	(0.588)
First fired 19-24 months ago	0.382	0.288	0.260	0.228
	(0.580)	(0.581)	(0.584)	(0.584)
First disabled 1-6 months ago	0.713	0.689	0.658	0.646
	(0.254)***	(0.254)***	(0.257)**	(0.257)**
First disabled 7-12 months ago	0.401	0.365	0.309	0.302
	(0.292)	(0.292)	(0.295)	(0.295)
First disabled 13-18 months ago	-0.372	-0.423	-0.416	-0.436
	(0.381)	(0.381)	(0.382)	(0.382)
First disabled 19-24 months ago	0.378	0.338	0.301	0.297
	(0.211)*	(0.212)	(0.213)	(0.214)
Observations	685769	685769	685769	685769

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Notes: Cox proportional hazard model for the relationship ending in a separation or divorce. The dummy variable "First laid off x-y months ago" is set to missing if the relationship was not observed at any time during the previous y months; all other dummy variables in the table are set to missing according to this same rule. Wage and labor force participation controls are: average earnings for the past 12 months, number of months unemployed in the last 12 months, and number of months inactive in the last 12 months. Columns 3 and 4 use a stratified Cox model. The controls that are stratified on are: house ownership dummy, a dummy taking the value 1 if only one of the partners is a high school dropout or if both partners are high school graduates, a dummy taking the value 1 if one of the partners is a high school graduate and the other has some college education, a dummy taking the value 1 if both partners have some college education, and a dummy taking the value 1 if a married couple ever cohabited. The other controls in column 3 are: number of couple's own kids under 18 interacted with a quadratic in relationship duration, whether there are other kids in the household besides the couple's own, married dummy, age at the beginning of the relationship, age difference between the partners (set of dummies: woman older by 5 years or more, man older by 5 years or more), white man dummy, same race dummy, and an interaction of a dummy for people who live together but never marry and a dummy for the survey year being before 1996. All individual-specific controls are separated into woman's and man's. Column 4 includes the controls from column 2 and 3.
Source: Survey of Income and Program Participation, 1990, 1991, 1992, 1993, 1996, 2001.

Figure 6: Non-parametric estimates of the impact of labor market shocks as a function of relationship duration



Notes: Cox proportional hazard model for the relationship ending in a separation or divorce. The graph plots smoothed scaled Schoenfeld residuals for various labor market shocks. The specification used is the same as in Table 3, column 4.
Source: Survey of Income and Program Participation, 1990, 1991, 1992, 1993, 1996, 2001.

Figure 7: Distribution of marital happiness for women, at varying relationship durations

Notes: 1 corresponds to “very unhappy” and 7 to “very happy”.
Source: National Study of Families and Households 1987-1988, cross-section.