Dynamic Optimization in Models for State Panel Data: A Cohort Panel Data Model of the Effects of Divorce Laws on Divorce Rates

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Key words:marriage and divorce, divorce laws, Coase Theorem, state panel data, dynamic models

June 29, 2011

Abstract

We present a new approach to the estimation of dynamic models using panel data, not on individuals, but aggregated to some level such as the school, county or state. This approach embeds the reduced form implications of dynamic optimization for exiting a chosen state (via divorce, dropping out, employment, etc.) into a model suitable for estimation with state panel data or similar aggregates (county, SMSA, etc.). With forward looking behaviors, exogenous changes in laws or rules give rise to *selection effects* on those considering entry and *surprise effects* for those who have already entered. Our application is to the effects of divorce laws on divorce rates.

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†Our thanks to Maria Casanova, Chris Flinn, John Kennan, Johnathan Klick, and Seth Sanders for insightful comments as well as participants at both the Summer 2009 Workshop of the Institute for Research on Poverty at the University of Wisonsin and the Fourth CELS meeting at USC, November 2009. Thanks also to Deborah Rho for excellent research assistance.

Contents

1 Introduction

The economic model and the emprical specification developed in this paper are applicable to a wide range of problems much more general than the particular application to divorce studied here. This cohort panel data model (CPDM) lives in the sparsely populated space between the estimation of fully articulated dynamic maximization models and the estimation of much simpler difference-in-difference models. As shown in the current application, the CPDM provides a rich framework with which to articulate and estimate the implications of dynamic models.

The CPDM embeds the reduced form implications of dynamic optimization for exiting a chosen state (via divorce, dropping out, employment, etc.) into a model suitable for estimation with panel data, not just on micro panel data but on data aggregated to some level such as the school, county or state. With forward looking behaviors, exogenous changes in laws or rules give rise to *selection effects* on those considering entry into a state and *surprise effects* for those who have already chosen to enter. Following a surprise, unobserved within-cohort heterogeneity gives rise to *floodgate effects,* an immediate spike in the exit rate followed by a decline. Key to the resulting cohort panel data model (CPDM) is tracking differential selection embodied in entry cohorts.

The application is to the effect of divorce laws on divorce rates. Whether divorce law liberalizations caused the increase in divorce rates remains controversial.[1] One factor contributing to the controversy is data. For want of good geocoded micro panel data, researchers have resorted to panels of geocoded regional averages (school, county, state,). Prior to this study, this meant that insights from dynamic models have only been loosely tied if at all to the econometric specifications.[2] A second factor is a methodological gap between difference-in-difference approaches and methods explicitly grounded in dynamic optimization applied to micro panel data.[3] Drawing on positive features of both methods, this study attempts to help to bridge this gap.

This research helps to clarify whether and how divorce laws should be used in future empirical work, a matter of great practical importance. For example, contemporaneous unilateral divorce law has been used to study intrahousehold distributions (Chiappori, Fortin, and Lacroix 2002). Others have studied the effect of unilateral laws per se on child well being and on crime (for example, Gruber (2004), Caceres-Delpiano and Giolito (2008a), and Caceres-Delpiano and Giolito (2008b)). This study calls this practice into question as we soundly reject the enabling assumption (or interpretation of previous empirical results) that unilateral laws cause divorce.

Drawing on the structural models of marriage and divorce of Rasul (2008) and Weiss and Willis (1997), we embed the implications of dynamic optimization in a reduced form, linear probability model of an individual's divorce probability. In this reduced form, liberalizations in state laws

[1] Gruber (2004), for example, felt compelled to first offer evidence that unilateral laws cause divorce before proceeding to analyze how these laws affected children. Other authors have dismissed unilateral law as a cause of divorce (Brown and Flinn 2006) (Tartari 2007). Others appealed to the Coasian arguments of Becker (1981), Peters (1986) and others, e.g., Weiss and Willis (1997).

[2] A well known exception is Wolfers (2006) who appended a dynamic lag structure to unilateral divorce dummies. Further, he provided an erudite and comprehensive discussion of all the possible dynamic channels potentially manifested in his lag coefficients. However, since these channels are all mixed together in each lag coefficient, even if we knew the "true" values of these coefficients, we would be hard put to say that we have pinned down the effects of any particular channel.

[3] Rasul (2006) expressed this gap. Having laid down a model of optimal timing of marriage and divorce and the effects of unilateral law thereon, he expressed deep reservations about our ability to learn about these effects from the likes of state panel data.

determined both the cost of divorce and the right to divorce. Key to the analysis is the concept of a marriage cohort - all those married under the same divorce law regime. A given cohort selects into marriage on the basis of both the costs and rights to divorce. Later on during marriage, liberalizations in costs and rights that were unanticipated at the time of marriage increase divorce probabilities. Our goal is to estimate this model using state panel data. The issue is how to aggregate to the state level without forfeiting the distinctions between the selection and surprise effects associated with both costs and rights.

Our aggregation protocol is key. We aggregate (within state) first to the marriage-cohort level. Then, each cohort is weighted by its time-varying contemporaneous share in the state population and aggregated to the state level. The resulting cohort panel data model (CPDM) is quite generally applicable. In the absence of micro-panel data, the CPDM enables researchers who must resort to state (city, county, country) panel data to preserve and estimate the reduced form implications of the underlying structural dynamic model.

Integral to our application of the CPDM to divorce is our new index of the cost of establishing grounds for divorce. Applicable to all divorce regimes (fault or no-fault; and if no-fault, then bilateral or unilateral), the cost index enables us to make a clear distinction between the costs of divorce and the right to divorce, a distinction that has been muddled in previous work. It also enables a ceteris paribus test of the Coase Theorem (that the adoption of unilateral law will not change divorce rates holding constant both cost surprises and selection into marriage).

Also, integral to our application of the CPDM to divorce are what we call floodgate effects. Following the liberalization of divorce laws, the presence of heterogeneity in the quality of marriages within marriage-cohorts leads to a distinct time-pattern. Immediately following the liberalization, divorce rates spike and then decline, eventually declining to a level between the relatively low level preceding the liberalization and the peak rate at the spike.

The CPDM for state divorce rates nests three important empirical specifications. (i) If the role of within-cohort unobserved heterogeneity plays no role, the homogeneous CPDM results. (ii) Imposing the equality of selection and surprise effects for both costs and rights collapses the CPDM to a static model in which case only contemporaneous changes in divorce law matter. The further restriction, eliminating costs altogether, leads to the Friedberg (1998) canonical specification.

Interestingly, with floodgate effects included, the CPDM does not nest the specification of Wolfers (2006) in which lagged rights determine divorce rates. Nor does it nest a generalization of his model in which lagged costs determine divorce rates. Hence it seems a stretch to interpret his results on lagged effects in some of the ways that he did.

In addition to pulling these and other earlier specifications together under the umbrella of the CPDM, these nesting results enable us to explain the conflicting empirical evidence across previous studies generally and for tests of the Coase Theorem in particular. Differences between those results and ours stem from both omitted variable bias and unwarranted parameter restrictions. The latter lead to the improper aggregation across marriage cohorts.

With regard to data, we started with Gold (2008) and his careful coding based on his reading of the state laws. We made some changes to make the coding based on our own reading of not only the legal codes but also on subsequent court cases. Moew importantly, the way we actually use the coding of the laws – as dictated by the CPDM and our focus on costs and rights – differs substantially from our predecessors. The coding presented in Section 6.2 below is congruent with the two effects we wish to measure, those of rights and those of the costs of establishing grounds for divorce. A second new aspect of our data is the construction of time-varying marriage cohort shares from the CPS.

To preview the resulting estimates of the CPDM and related models we find (i) strong support for the cost-minimization assumption underpinning our cost index; (ii) the inclusion of our cost of divorce index wipes out the significance of unilateral laws in both static and dynamic models; (iii) strong support for the trio of hypotheses that embody the Coase Theorem (unilateral law has no selection effects on marriage quality, there are no surprise effects from the contemporaneous adoption of unilateral law, and there are no associated floodgate effects following the adoption of unilateral law); (iv) robust evidence that unanticipated reductions in divorce costs increase divorce rates; (v) evidence that floodgate effects following these cost surprises; and (vi) evidence that lowering divorce costs decreases the quality of the marginal marriage and thereby increases divorce rates. Finally, (vii) regarding rejections of the Coase hypothesis in earlier studies, we account for the differences between our results and those in earlier studie by showing the earlier estimates suffer from omitted variable bias as well as improper aggregation over marriage cohorts.

In addition, the CPDM highlights the profoundly contradictory nature of policy levers. Policies designed to reduce exit rates (e.g., divorce) may have the unintended consequence of reducing subsequent entry rates (e.g., marriage). Conversely, policies designed to promote entry (e.g., marriage) may have the unintended consequence of increasing subsequent exit rates (e.g., divorce).

We acknowledge up front limitations of this study. With regard to the exogeneity of divorce laws, we maintain, as have others, that the timing of changes in the laws were exogenous, but not necessarily the type of law passed by each state.[4] To maintain comparability with previous studies we stick to the main laws governing divorce studied in the progression of studies leading to this one,[5] namely the right to divorce and the cost of divorce. Thus, we abstract from marital property laws (Gray 1998), the adoption and enforcement of child support laws (Sun 2008), taxes and transfers (Dickert-Conlin and Houser 2002), and the potential deconstruction of fault laws.[6]

The remainder of this paper is organized as follows. Section 2 presents some stylized facts, a brief history of the divorce revolution, and a taxonomy for US state divorce laws leading to a our index of divorce costs. Starting with the implications of dynamic optimization for individual divorce probabilities, Section 3 aggregates these first to the cohort and then to the state level, culminating in the CPDM for state divorce rates. This includes modeling the effects of heterogeneity in marriage quality leading to "floodgate effects." Section 4 establishes the relationships between the CPDM and earlier models and shows that unlike earlier models, the CPDM can deliver an unbiased and consistent test of the Coase Theorem. Section 5 sets forth maximum likelihood estimators for state panel data when key parameters of costs must be estimated. Section 6 briefly presents the newly coded divorce data and construction of the time-varying marriage cohort shares. Section 7 gives the main empirical results and Section 8 concludes.

[4] Even though a state's 1968 divorce rate is a good predictor of whether or not a state subsequently adopted unilateral divorce, Friedberg (1998) found that the timing of divorce law changes were exogenous. To absorb unobserved correlates, she implemented year fixed effects, state fixed effects, and state-specific linear and quadratic time trends. Apart from our addition of state-specific first autocorrelation, we do the same.

[5] These include Gold (2008) as well as Peters (1986), Friedberg (1998), and Wolfers (2006).

[6] Courts were strict about sticking to the legislated admissible grounds. Friedman (1984) in making this point documents, for examples, cases in which states that only accepted "proof" of adultery declined to accept other grounds. In particular he cites cases in which blatant and extreme physical cruelty and bald-faced mutual hostility were inadmissible and therefore divorces were not granted, even though both parties wanted to divorce. Thus there may be mileage in differentiating amongst no fault grounds on the basis of how costly each one is to "prove" in court.

2 Some history and a taxonomy for US divorce laws

2.1 The Good Old Days: De Facto vs. De Jure

For comparability with previous studies our sample period is 1962-1988[7]. As of 1962, in all but three states the right to divorce was held bilaterally by a married couple.[8] Grounds for divorce always included adultery and many states included several additional unsavory behaviors. Grounds were established in court by one spouse proving the other guilty (at fault) based on the grounds that were available in their state. Most did not, but 18 states provided an additional ground for divorce, namely living separate and apart[9] for a specified minimum number of years, hereafter called the wait time. Wait times were generally long. The modal wait was 5 years and one state specified 10 years. Whether or not a wait time was grounds for divorce, we call this configuration of laws *bilateral-fault law*, or simply *Regime I* or R^I.

Regime I laws were intended to protect and promote the sanctity of marriage. In practice they functioned as a rather expensive barrier to be circumvented. The legal historian, Lawrence Friedman [1984, p. 659] described the practice of divorce law under bilateral-fault laws with long wait times or no wait times thus:

> The main element was simply collusion between husband and wife, and among husband, wife, lawyers and judges. In strict states [Regime I with long waits or no waits], this collusion took drastic and distasteful forms. In New York, divorce required adultery. A minor industry sprang up churning out imitation adultery and genuine perjury. There was enough real adultery in New York, no doubt to meet consumer demands. But real adultery hurts reputations, washes dirty linen in public, and gets too close to the bone. Fake adultery was more acceptable. There were lawyers who, for a fee, arranged little scenes in hotel rooms, with women posing for incriminating photographs. Henry Zeimer and Waldo Maison, arrested in 1900, ran a business that hired and coached women to get on the stand, testify they know the husband in the case, blush, cry, and then leave the rest to the judge.[10]

And on pages 662-3 he wrote:

> In almost every state, perjury or something close to it was a way of life in divorce court. The overwhelming majority were collusive and consensual, in fact if not in theory. The legal system winked and blinked and ignored. It was, in the first instance, collusive and underhanded; it was also irrational and unfair. It was costly for people who wanted divorce. Divorce was expensive in all sorts of ways, but thousands were willing to pay the price.[11]

[7] For optimal comparability with Wolfers (2006), we would have used 1956-1988, however, availability of CPS data preclude this.

[8] Also known as mutual consent fault laws.

[9] Meaning, without intimacy.

[10] Later he wrote of a 1934 article from the *NY Sunday Mirror* entitled, "I was the Unknown Blonde in 100 Divorce Cases," *Virginia Law Review*, vol. 86, no., 2000, p. 1512.

[11] One of the expected costs had to do with the collusive agreements going awry. Friedman recounts the case of Hester and Garder Jones. Hester wanted the divorce. Gardner protested he was framed. He had however dutifully gone to the hotel room but stayed three days, explaining lamely that he "thought the detectives were coming sooner than they did," p 660.

In addition to Friedman, various authors, including Rheinstein (1972) and Sugarman and Kay (1990) have described the routine of finding almost always, the husband[12] guilty of the offense in a short trial where the accused did not appear. Although proscribed by law, collusion of the husband and wife is the only way to explain this and courts were at a loss to prevent collusion. Rheinstein, for example, writing just after California adopted unilateral law, detailed and bemoaned just how difficult, even hopeless, it was for the court to question sworn statements of adultery, desertion, cruelty, and other intimate details of a marriage.

Under bilateral fault laws, even if wait-times were on the books, these long wait times were generally not used, thus revealing that proving fault in court was a less onerous route than waiting for long periods. With or without wait-times on the books, behavior was the same. The husband, the wife, their respective lawyers and the judges cooperated in a sham court proceeding in which one spouse "proved" the other was at fault. What was "proven" generally had little relationship to the actual reasons for divorce. Judges, by and large made short work of the requisite court proceedings. The de facto cost of divorce was the cost of this sham, including disutility from knowingly perjuring oneself and uncertainty of the outcome as well as other pecuniary and nonpecuniary costs. The real enforcement of "bilateral" or "mutual" consent came from the power of either spouse, and particularly a spouse who would have rather maintained the marriage, to upset the proceedings. Generally property and custody agreements were worked out in advance (Fonzo 1997), (Friedman 2000), (Friedman 1984).[13]

2.2 The divorce revolution

Beginning in the 1960's and especially during the 1970's, many states moved to liberalize their divorce laws. Dubbed the "divorce revolution," this era saw soaring divorce rates. Figure 1 shows the crude divorce rates (from top curve to bottom) for California, the US as a whole[14], and North Carolina from 1956-1998. For the US as a whole, a well-known pattern emerges. In the early 1960's divorce rates began to rise, roughly doubling before their peak in 1981 and trending slowly down thereafter. Note that as illustrated with California and North Carolina, until the late 1980's, state trends seemed to be vertical displacements of the national trend, but not thereafter.

Can legal changes account for these patterns? Some hints appear in the graph. The vertical bar in 1965 coincides with a notable spike in NC's divorce rate. North Carolina implemented a reduction from two years to one in the minimum time couples had to wait separate and apart to establish grounds for divorce. More famously, California passed unilateral divorce laws in 1969 and implemented the law January 1, 1970. This was accompanied by a well known spike in California's divorce rate in 1970.

[12] There is much evidence that couples took the least cost route. For example, the accused was always the husband because it sullied his reputation less. The offense was the least sordid ground permitted by the state; see Friedman (2004)

[13] See Friedman (2000) for an especially insightful account and a good read.

[14] The national rate is the population-weighted average of the individual state divorce rates, from Wolfers' website. He, in turn, got the state divorce rates from 1968-88 from Friedberg and, following Friedberg (1998), constructed the earlier rates from Vital Statistics.

NC US divrtsovertime-

stwts

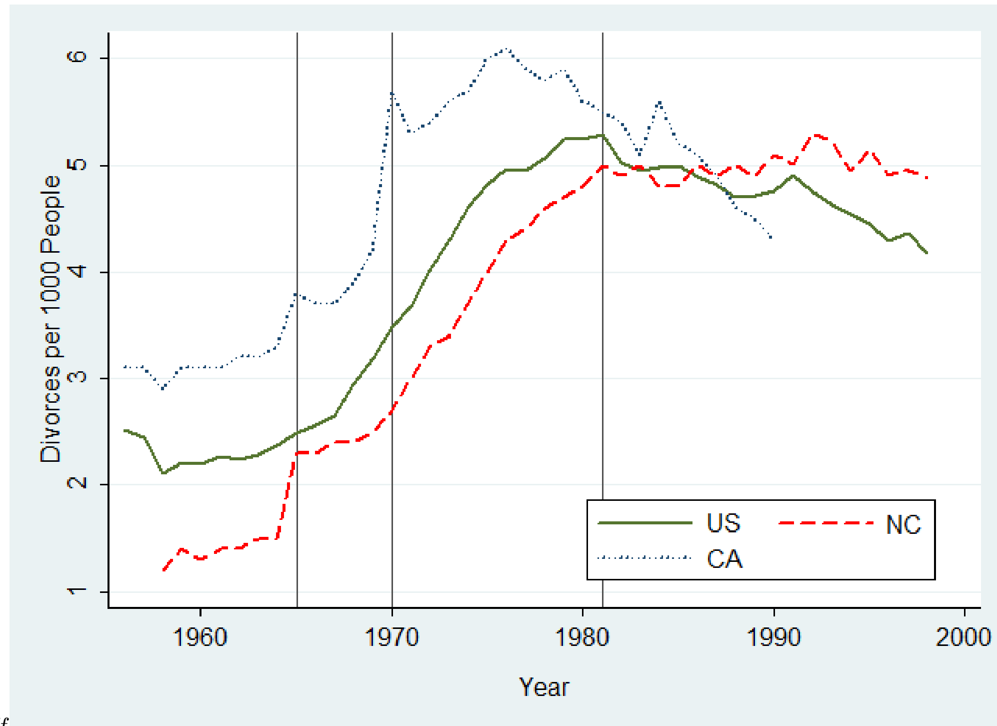

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Figure 1: Divorce rates for CA, the Nation, and NC; 1956-98.

2.3 Taxonomy and cost index for US divorce laws

As for example in Rasul (2006) and Weiss and Willis (1997), in a dynamic theory of divorce the crucial comparison is between the value of continuing the marriage and the value of divorce. The systematic variation in this spread across states and over time for a given state is determined, in part, by the *cost of establishing grounds for divorce*, henceforth simply the *cost*. These costs, in turn, depend on admissible grounds for divorce: (i) waiting a specified number of years, (ii) proving fault or (iii) establishing no-fault grounds.

		No-Fault Grounds Available?	
		No	Yes
		Fault state	No-fault state
RIGHT	Bilateral	R^I Prove fault or wait w years $(0, \omega_{st})$	R^{II} Establish no-fault grounds $(0, w^N)$
RIGHT	Unilateral	■	R^{III} Establish no-fault grounds $(1, w^N)$

Table 1: Taxonomy of Divorce Regimes
[15]

As displayed in Table 1, our taxonomy for state divorce laws gives equal billing to costs (grounds for divorce) and the right to divorce. Laws are characterized by the right to divorce – bilateral or unilateral (the rows) and by whether or not no-fault grounds are available (the columns).

Bilateral laws (first row) require bilateral (or mutual) consent of both spouses, thereby conferring the right to divorce on the spouse who wants to maintain the marriage. In contrast, unilateral laws (second row) permit either spouse to file unilaterally, thereby conferring the right to divorce on the spouse who wants to leave.

Fault grounds always included adultery and often included additional unsavory behaviors such as habitual drunkenness, cruelty and so on.[16] No fault grounds include irreconcilable differences, incompatibility, irretrievable breakdown and synonymic phrases.[17] The blank cell in the lower left indicates that no states have a unilateral right to divorce yet require proof of fault. Rather, unilateral rights constitute a special case of no-fault law. As shown in Table 1, we denote the three resulting divorce law "regimes" as R^I, R^{II}, and R^{III}.

As noted above, in some Regime I (bilateral-fault) states, as an alternative to proving fault, couples could establish grounds for divorce by waiting separate and apart (i.e., little or no intimacy) for a prescribed minimum number of years. We denote such *wait times* in state s at time t with w_{st}. If wait times were long, couples went to court and "proved" fault. If wait times fell below a critical value, w^*, couples fulfilled the wait time to establish grounds for divorce. Let ω_{st} be the cost of establishing grounds for divorce in R^I_{st}. Then

[16] Rheinstein (1972) catalogued 37 different unsavory behaviors that constituted fault in at least one state.

[17] Some states added no-fault grounds to fault grounds. In these cases, cost minimizing behavior insures that once no-fault grounds are admitted, the admissabililty of fault grounds becomes irrelevant. Therefore such states are classified as no-fault.

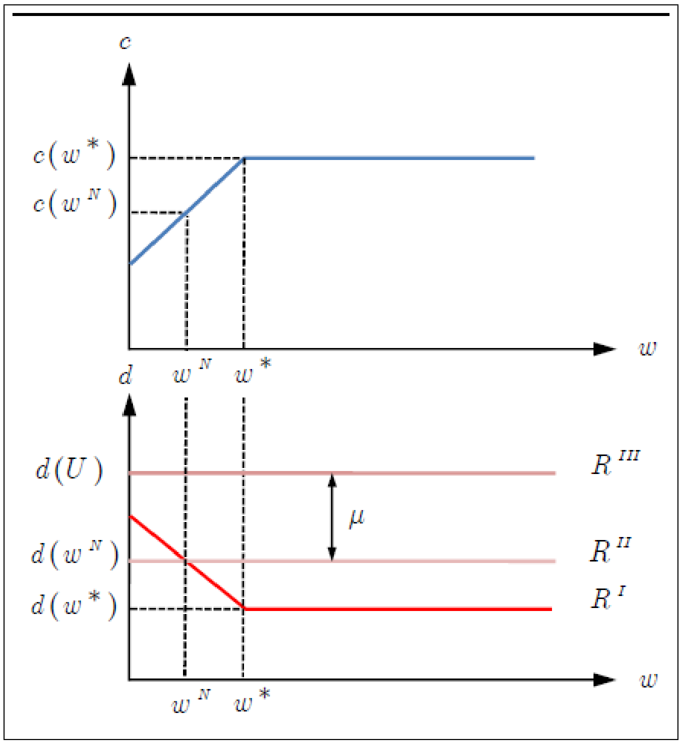

Figure 2: Costs and divorce rates as functions of wait times

$$\omega_{st} = \omega(w_{st}, w^{*}) = w_{st} + (w^{*} - w_{st})\, I\,(w_{st} > w^{*})\,. \tag{1}$$

The critical value w^* is the wait-time equivalent (in terms of utility) of going to court and proving fault.

The behavior in states in Regime I that had no wait time alternative was the same as in states with long wait times as defined as all times longer than w^*. Thus, for states that had no wait times, we can assign any "long" wait time to these state-year combinations. In practice, we assigned 8 or 10 year waits to these state-years These values are above the mode of wait times prevailing in the early years of our sample. Given this assumption, (1) completely characterizes cost in Regime I.

The upper panel in Figure 2 graphs the cost of divorce against wait times. It is kinked at w^*. For waits greater than w_*^I, "proving" fault is cheaper than waiting, and the cost at w^* is the upper bound on costs. For wait times shorter than w_*^I, waiting is the cheaper option. If divorce rates were a linear function of contemporaneous costs, then divorce rates in Regime I would look like the lower graph in Figure 2, inheriting a kink at w^* from the cost function.

In Regimes II and III, couples face the cost of establishing no-fault grounds. Let w^N be the wait time at which a couple is just indifferent between establishing no fault grounds and waiting w^N years to establish grounds. Henceforth we call w^N *the cost of establishing no-fault grounds.*

In summary, cost minimizing behavior yields the following wait-time index of the cost of establishing grounds for divorce,

$$c_{st} = [w_{st} + (w^{*} - w_{st})\, I\,(w_{st} > w^{*})\, c_{st}]\, R^{I} + w^{N}\left(R_{st}^{II} + R_{st}^{III}\right). \tag{2}$$

Since $R^I_{st} + R^{II}_{st} + R^{III}_{st} = 1$, the divorce law for any regime can be characterized by the tuple (U_{st}, c_{st}). In Table 1, the last line in each cell records this characterization. Finally, note that this is a broadly defined index of costs. For example, for a wait-time of w^* years, the utility cost includes psychological as well as financial costs, mental anguish and so forth.

2.4 Three paths to easy divorce

Between 1956 and 1988 nearly every state, save three, liberalized its divorce laws. As of 1956 those three states already had unilateral no-fault laws. The remaining 48 had bilateral fault laws. Of these 48, only 18 recognized minimum wait times as grounds for divorce and these times were long - the modal wait was five years and the maximum was 10. By 1988 all states had some form of easy divorce.

How did 48 states transit from laws that made divorce difficult and expensive to laws that made divorce relatively easy? Using our taxonomy and coding of the laws (for coding see Section 6.2), these transitions are described by three paths. Twelve states took "Path I". They remained in Regime I (bilateral fault laws), but adopted short waits. By 1988 the average wait was down to 1.25 years. Another six states took "Path II"; they moved to Regime II, retaining mutual-consent laws but accepting no-fault grounds for divorce. The no-fault grounds were sometimes in place of and other times in addition to the older fault grounds. Finally, 33 states took "Path III"; they adopted unilateral no-fault laws and thereby moved to Regime III.

Note that a number of states got to their final regime in steps. For example, Delaware started in Regime I with a three year wait, dropped this to 1.5 years in 1968 and finally completed Path II with the adoption of no-fault grounds in 1975.

In sum, the three paths to easy divorce were:
Path I : $R^I \rightarrow R^I$; adopted and or lowered wait times to about 1 year.
Path II : $R^I \rightarrow R^{II}$; adopted no-fault grounds, maintained bilateral consent
Path III : $R^I \rightarrow R^{III}$; adopted no-fault grounds and changed to a unilateral right to divorce.

Figure 3 graphs the divorce rate for states on each of these paths. Note that up through about 1980 or 1981, these three paths are roughly parallel, with Path I and Path II states closely resembling each other and Path III states being higher but exhibiting the same trends. After that, the divorce rate for states that adopted unilateral law (Path III) trends downward slightly more steeply than the divorce rates for the other two paths.

2.5 Ideal quasi-experiment for testing the Coase Theorem

Peters (1986) recognized the invariance of divorce rates with respect to the adoption of unilateral law as an application of the Coase Theorem and emphasized that the changes in divorce laws provided a rare opportunity to test this Theorem. The ideal quasi-experiment for testing the Coase Theorem would be to observe the change in divorce rate as a states passed from R^{II} to R^{III}. These states would have no-fault grounds both before and after adopting unilateral rights. *Unfortunately, no state made this transition.* Hence, holding costs constant while testing the Coase Theorem requires a model such as the one presented here.

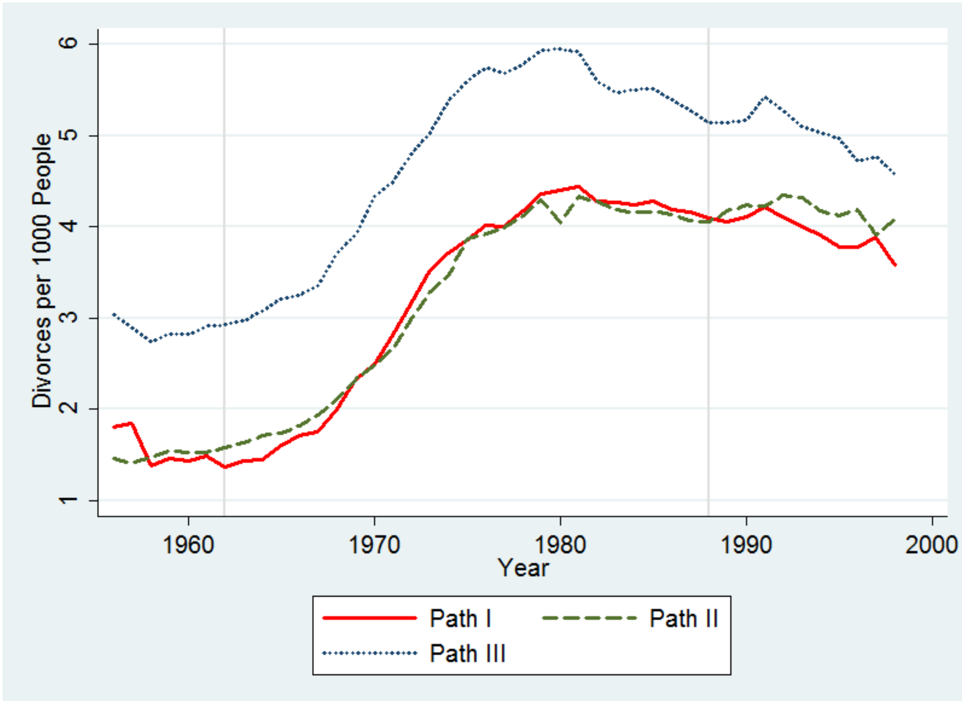

Figure 3: Population-weighted divorce rates for states on three paths.

3 Implications of dynamic optimization for state panel data

At the level of the individual decision maker, our reduced form model is inspired by and draws on the implications of two dynamic optimization models of individuals' search, marriage, and divorce behaviors: (i) Rasul (2006)'s model (henceforth, just Rasul) that focused on the selection effect of unilateral law on marriage and the subsequent impact on divorce rates and (ii) Weiss and Willis (1997)'s model (henceforth, W&W) that focused on the impact of post-marriage surprises (in their case, wage surprises) on divorce probabilities. Although the first is based on nontransferable utilities and the latter on transferable utilities, these value-function based decision models have remarkable commonalities and our reduced form clearly draws on both.

Our model encompasses the effects on contemporaneous divorce rates of both *selection* and *surprise* effects. Laws are modeled as having two dimensions: (a) the *right to divorce* (whether the right is bilateral or unilateral) and (b) the total *cost of divorce* as captured by our cost index. One shared caveat is that their models and ours rely on the assumption of static expectations: at the time of marriage individuals do not anticipate subsequent changes in divorce laws. In addition we abstract from both remarriage possibilities and life-cycle effects.

This section proceeds as follows. First, drawing on these models, we capture the salient implications of dynamic optimization in a reduced form linear probability model of individual divorce. Then, within a state, individual divorce probabilities are aggregated to the marriage-cohort level – all those married under the same divorce regime. In aggregation to the cohort level, unobserved heterogeneity in marriage quality yields floodgate effects. This time pattern of responses to a surprise liberalization of the law consists of an immediate spike in the divorce rate followed by an extended decline. Finally, further aggregation, from the marriage cohort to the state level, yields the cohort panel data model (CPDM) for state panel data. Substituting out the cost index from above, we particularize the CPDM to state panel data on divorce rates. Inherited from the cost specification, these state divorce rate functions are kinked at w^*. Parameters to estimate include two cost parameters, w^* and w^N, as well as the *selection effects of rights, the selection effects of costs*, the *surprise effects of rights, and the surprise effects of costs,* and the *parameters of the floodgate effects.*

3.1 Dynamic optimization - individual level

To establish notation, for individual i, living in state s at time t (henceforth, "in (s,t)") we indicate the probability of divorce as d_{ist} , the cost of establishing grounds for divorce as c_{ist} , the unilateral right to divorce as $U_{ist} = 1$ and the bilateral right with $U_{ist} = 0$. In addition individual i has two time-invariant characteristics, c^m_{is} and U^m_{is}, the cost of divorce and right to divorce when i married.

Pre-marriage *selection* into marriage. Given static expectations, *selection effects*[18] relate the contemporaneous divorce probabilities (d_{ist}) to the divorce laws at the time of marriage (U^m_s, c^m_s).

As shown by Rasul, the lower the cost of divorce anticipated during marriage, the higher the (present discounted) value of the divorce option as well as the value of marriage conditional on remaining married. The higher this value, the larger the number of couples who take a chance on marriage and the lower the quality of the marginal marriage. These marginal couples (who would not have married except for low divorce costs) are less well buffeted against destabilizing shocks than are the inframarginal couples (who would have married even in the absence of lower divorce costs). Subsequently, these marginal couples have higher divorce rates than the inframarginals, thereby pulling up the overall divorce rate. Since marriage quality is unobservable and expectations are static, other things equal, the probability of divorce for a randomly selected individual i will be higher the lower was the cost of divorce when i married. Thus, for the reduced form, we represent the *selection effect of lower divorce costs at marriage* as $\beta' \equiv \frac{\partial d_{ist}}{\partial c^m_s} < 0$. As costs fell over time, selection effects would tend to increase divorce rates.

Turning to selection based on the right to divorce, only if divorce is inefficient would a change from a bilateral to a unilateral right to divorce change the probability of divorce; see Becker (1981) and earlier, Peters (1986). As Rasul argued, the change from bilateral to the unilateral right relieves married individuals of one risk but forces another upon them. Individuals no longer run the risk of being stuck in a no-longer-wanted marriage. Instead, they bear the risk of being deserted by their spouse. In Rasul's model, whether this trade reduced the value of marriage was ambiguous. He, nonetheless, made a strong empirical case that the value of marriage fell. So while the sign of this effect is to be determined empirically, until shown otherwise, we will assume that the adoption of unilateral law decreases the value of marriage. Given this, then the adoption of unilateral law would cause some couples who would have married had the law not changed, to forego marriage. These forgone marriages would have been of lower quality than the marriages that took place under unilateral law. Hence, in the subsequent periods, the absence of these marginal marriages reduces

[18] Our selection effects due to unilateral law are what Rasul called indirect effects.

the divorce rate. Thus, the *selection effect of the adoption of unilateral law* on the contemporaneous probability that i divorces is[19] $\mu' \equiv \frac{\triangle d_{ist}}{\triangle U_s^m} \leq 0$. The corresponding thought experiment is the difference in the divorce rates for two observationally equivalent individuals, except that one was married under $U_s^m = 1$ and the other under $U_s^{m'} = 0$.

Post-marriage *surprises.* The surprise effect of lowering divorce costs relates the contemporaneous divorce rate (d_{ist}) to the size of the contemporaneous surprise in the cost of divorce ($c_{st} - c_s^m$). Historically (with one trivial exception), divorce costs fell over time, so that cost surprises are negative or zero, $(c_{st} - c_s^m) \leq 0$. Other things equal, the contemporaneous effect of a negative surprise is to increase the (present discounted) value of divorce relative to the continuation of marriage, thereby increasing the probability of divorce. Hence, the *effect of a surprise lowering of divorce costs* is to increase the divorce probability, or $\beta \equiv \frac{\partial d_{ist}}{\partial(c_{st} - c_s^m)} < 0$ so that $\beta(c_{st} - c_s^m) \geq 0$.

The surprise effect of adopting unilateral law relates the contemporaneous divorce rate (d_{ist}) to a post-marriage change in the right to divorce, $(U_{st} - U_s^m)$. As all states that adopted unilateral laws started with bilateral laws and never switched back. Thus, the surprise, $U_{st} - U_s^m$, takes on the value of 0 or 1, but never -1. If divorce decisions are inefficient, then under bilateral law, some individuals may have been stuck in marriages they no longer wanted; upon the adoption of unilateral law, they can divorce. Hence other things equal, the *surprise effect of the adoption of unilateral law is* $\mu \equiv \frac{\triangle d_{ist}}{\triangle(U_{st} - U_s^m)} \geq 0$.

As noted by Becker and Peters, and driven home by Rasul, the Coase Theorem predicts that with costless transfers and symmetric information on outside options, *for those already married,* the adoption of unilateral law (the surprise) will not affect the divorce rate, or $\mu = 0$. Note that our surprise term $(U_{st} - U_s^m)$ is quite distinct from the conventional dummy, U_{st}. For example, the rights surprise is always zero for those married in the last (5^{th}) divorce regime, regardless of whether or not their state adopted unilateral law. As detailed later, in the light of our model and empirical results, prior tests of the Coase Theorem based on the contemporaneous dummy, U_{st}, are biased and inconsistent.

A linear approximation to the reduced-form probability of divorce. Gathering all four effects together (selection and surprise crossed with costs and rights), write the linear approximation to the reduced form probability that individual i in (s, t) who was married under regime (U_s^m, c_s^m) divorces as

$$d_{ist} = \alpha + \underset{(-)}{\beta'} c_s^m + \underset{(-)}{\mu'} U_s^m + \underset{(-)}{\beta} (c_{st} - c_s^m) + \underset{(+)}{\mu} (U_{st} - U_{is}^m) + X_{ist}\eta + \epsilon_{ist}. \tag{3}$$

Here the signs of parameters are shown in parentheses, X_{ist} is a row vector of individual and state characteristics that may vary over time with corresponding parameter vector η, and ϵ_{ist} is an *i.i.d.* mean zero random error with constant variance.[20]

[19] Rasul called this the *indirect* effect of the adoption of unilateral law.

[20] Ideally (3) would include interaction terms. Such terms would be of second order of importance. Moreover, in our application, these would likely overparameterize the model relative to the rather unrefined information content of state panel data. As specification (3) already pushes the limits of what we can learn from a state panel on divorce rates, we choose, instead to spend our degrees of freedom on the more fundamental parameters, $w^*, w^N, \beta', \mu', \beta$ and μ as well as a nonparametric representation of unobserved within cohort heterogeneity detailed below.

3.2 Dynamic optimization - cohort level and floodgate effects

Divorce Regimes, Marriage Cohorts, and Marriage-Cohort Shares. To avoid details of no consequence to our study, this discussion pertains to our sample periods (1956-1988 and 1962-1988). Prior to 1988, all states changed their divorce laws once or more, with four being the maximum. Call each distinct set of divorce laws a *regime,* with successive regimes separated by a change in the law. For state s, the m^{th} *legal regime* is (U_s^m, c_s^m). For convenience later on, we adopt the following numbering convention. Set $m = 1$ for the first regime. And, *set* $m = 5$ *for the regime in place at the end of our sample period, regardless of how many times a state changed its divorce laws.* Thus, if a state changed its laws once, before the change we have regime $\left(U_s^1, c_s^1\right)$ and after the change $\left(U_s^5, c_s^5\right)$. If a state changed its laws twice, then we have regimes $\left(U_s^1, c_s^1\right), \left(U_s^2, c_s^2\right), \left(U_s^5, c_s^5\right)$; in this case we think of the missing regimes, $\left(U_s^3, c_s^3\right)$ and $\left(U_s^4, c_s^4\right)$ as arbitrary legal regimes that are never populated.

Corresponding to the m^{th} regime is the m^{th} *marriage cohort,* defined as all individuals married under regime (U_s^m, c_s^m) and as having population N_{st}^m. The 1^{st} marriage cohort is always the oldest and the 5^{th} the youngest. Further, in (s,t) define the m^{th} *marriage-cohort share* as the share of individuals who were married under regime (U_s^m, c_s^m), or $g_{st}^m = \frac{N_{st}^m}{N_{st}}$, where $N_{st} = \sum_{m=1}^{5} N_{st}^m$ is the total number of marrieds in (s,t) so that $\sum_{m=1}^{5} g_{st}^m = 1$. Continuing the example where a state changed its laws twice, the dummy regimes for $m = 2$ and 4 are always empty, or $N_{st}^m = g_{st}^m = 0$.

In addition, cohort shares are empty if they were not yet "born." That is, for cohort m^* to be populated in (s,t), the law must have already changed $m^* - 1$ times. (A trivial examples is that at $t = 1$, all marriage cohorts except the first are unpopulated.)

The systematic evolution of cohort shares plays an important role in the dynamics to follow. Upon the implementation of a new regime $\left(U_s^{m^*}, c_s^{m^*}\right)$, the $m^* + 1$ marriage cohort is born. Then, the size $N_{st}^{m^*+1}$and share of the marrieds, $g_{st}^{m^*+1}$ grows with every passing period until a new law is passed. At that point, membership in cohort $m_{st}^{m^*+1}$ is closed. Thereafter, divorce and death reduce $g_{st}^{m^*+1}$ with every passing period. Going beyond our sample period, with no further changes in the law, every cohort save the last one ultimately will shrink to zero.

We now turn our attention to the divorce rate in t for each marriage cohort.

Marriage-cohort divorce rates, homogenous marriage quality. Our first task is to find the cohort divorce rates for each cohort in (s,t). Barring within-cohort unobserved heterogeneity in the quality of marriages, we can average the divorce probabilities (3) across all individuals i in marriage-cohort m to obtain the m^{th} *cohort's divorce rate,*

$$d_{st}^m = \alpha + \beta' c_s^m + \beta\left(c_{st} - c_s^m\right) + \mu' U_s^m + \mu(U_{st} - U_s^m) + X_{st}^m \eta + \epsilon_{st}^m \ . \tag{4}$$

Here, since every individual in this cohort was married under (U_s^m, c_s^m) and now lives under regime (U_{st}, c_{st}), averaging over the individuals within a cohort is trivial for both selection and surprise terms. The averages for the remaining terms are $X_{st}^m = \frac{1}{N_{st}^m} \sum_{i=1}^{N_{st}^m} X_{ist}$ and $\epsilon_{st}^m = \frac{1}{N_{st}^m} \sum_{i=1}^{N_{st}^m} \epsilon_{ist}$.[21]

The cohort divorce rate (4) assumes no unobserved within-cohort variation marriage quality, a strong assumption. Hence we proceed to introduce heterogeneity.

[21] As ϵ_{st}^m is an average, heteroskedaticity across the cohorts emerges. However, we postpone the discussion of heteroskedasticity until we get to the state level of aggregation as there is no loss to doing so. Also note that this aggregation abstracts from interstate migration.

Marriage-cohort divorce rates with heterogenous quality: floodgate effects. Define *marriage quality* in the sense of Rasul and W&W as the ability of a marriage to survive negative surprises. Higher quality marriages are more likely to survive a given surprise than a lower quality ones. In general, we expect that within a marriage cohort, the quality of marriage differs across marriages in way that are unobserved by the econometrician. In the context of this unobserved heterogeneity, a surprise liberalization of a divorce law gives rise to what we term *floodgate effects.* These effects are characterized by a spike in the cohort divorce rate that accompanies an unanticipated liberalization of a divorce law, followed by the period by period decline in divorce rates, asymptoting out to a new equilibrium divorce rate.[22]

Appendix A sketches a simple model of unobserved heterogenous marriage qualities and the inexorable result, floodgate effects, emerges. The intuition runs as follows. Take a marriage cohort m in (s,t) and the surprise adoption of unilateral law. Suppose there are two marriage qualities with the higher quality marriages having a lower divorce rate. After a liberalizing surprise, for each quality the post-surprise divorce rate rises, producing an immediate spike in the overall cohort divorce rate. But since the divorce rate for a lower quality marriages exceeds that for higher quality marriages, relatively more higher quality marriages survive until the next period. This shifts the weights in the overall cohort rate away from the lower-quality marriages and toward the higher quality ones, thereby lowering the divorce rate as compared to the period before. Period by period, this differential weeding out of lower quality marriages reduces the overall cohort divorce rate. This pattern of response to a liberalizing surprise - an immediate spike followed by period by period declines - is a *floodgate effect.*

In the two-quality model in the appendix, with no further changes in divorce laws, over time the cohort's average divorce rate asymptotes out to the post-surprise divorce rate of the higher quality marriages. This new cohort equilibrium rate is in between: it exceeds the pre-surprise cohort divorce rate but is lower than the spike accompanying the liberalization. More generally, the numbers of distinct quality types, their frequency distribution, and their different divorce-rate responses to a surprise, will jointly determine the details of the decline following the spike (fast or slow, how low does it go on, and so forth).

As we have no economic prior on these factors, we represent the pattern nonparametrically by replacing the responses to surprises, β and μ in (4), with β^L and μ^L given by

$$\begin{aligned} \beta^L &= \beta L\left(l_{st}, \delta^{\beta}\right) = \beta\left[1 + \textstyle\sum_{k=2}^{K} \delta_k^{\beta} D_{kst}(l_{st})\right] \text{ and} \\ \mu^L &= \mu L\left(l_{st}, \delta^{\mu}\right) = \mu\left[1 + \textstyle\sum_{k=2}^{K} \delta_k^{\mu} D_{kst}(l_{st})\right]. \end{aligned} \tag{5}$$

Here, l_{st} denotes the elapsed number of periods between the current period, t, and the last time divorce law changed in s; the D's are dummies[23] that partition the lapsed time into intervals; and the δ's are unknown parameters to estimate that capture the floodgate effects nonparametrically.

[22] The effect of the surprise is analogous to opening a physical floodgate to let the water out - an immediate rush of water is followed by ever slower rates of flow until eventually the water levels behind and in front of the floodgate equalize.We owe a special debt to John Kennan who likely has forgotten that, for a crude predecessor of the current model, he gave this analogy. More importantly, he encouraged modeling and including such effects.

[23] For example, for lags of the form used by Wolfers and for $K = 7$ we would define $D_{1st}(l_{st}) = 1$ if state s's most recent law has been in effect for 1 or 2 years (i.e., if $l_{st} = 0$ or 1), $D_{2st}(l_{st}) = 1$ if the most reacent law has been in effect for 3 or 4 years (i.e., if $l_{st} = 2$ or 3),..., and. $D_{7st}(l_{st}) = 1$ if state s's most recent law has been in effect 15 or more years.

Thus, allowing for within-cohort unobserved heterogenous qualities of marriage yields the m^{th} *cohort's divorce rate* as

$$d_{st}^m = \alpha + \beta' c_s^m + \mu' U_s^m + \beta L\left(l_{st}, \delta^\beta\right)(c_{st} - c_s^m) + \mu L\left(l_{st}, \delta^\mu\right)(U_{st} - U_s^m) + X_{st}^m \eta + \epsilon_{st}^m \ , \qquad (6)$$

where the parameters δ^β and δ^μ capture the floodgate effects due to unobserved within cohort heterogeneity. Then (4) is the special case where $\delta^\beta = \iota$ and $\delta^\mu = \iota$ so that $L\left(l_{st}, \delta^\beta\right) = 1$ and $L\left(l_{st}, \delta^\mu\right)$ so the surprise coefficients reduce to β and μ.

If state divorce rates were available at the marriage-cohort level and if costs were directly observable, we would estimate (6) directly. As they are not, we next aggregate (6) to the state level and then tackle the measurement of costs.

3.3 CPDM for state divorce rates - observable costs

To aggregate the cohort divorce rates to the state level we use marriage cohort shares. Thus, in (s,t) weighting each cohort divorce rate d_{st}^m from (6) by the corresponding marriage-cohort share, g_{st}^m, and adding gives the state-level divorce rate in (s,t),

$$\begin{aligned} d_{st} &= \alpha + \beta' \sum_{m=1}^{5} g_{st}^m c_s^m + \beta L\left(l_{st}, \delta^\beta\right)\left(c_{st} - \sum_{m=1}^{5} g_{st}^m c_s^m\right) + \mu' \sum_{m=1}^{5} g_{st}^m U_s^m \\ &\quad + \mu L\left(l_{st}, \delta^\mu\right)(U_{st} - \sum_{m=1}^{5} g_{st}^m U_s^m) + X_{st}\eta + \epsilon_{st}, \\ &= \alpha + \beta' \sum_{m=1}^{5} g_{st}^m c_s^m + \beta L\left(l_{st}, \delta^\beta\right)\left(c_{st} - \sum_{m=1}^{5} g_{st}^m c_s^m\right) + \mu' g_{st}^5 U_s^5 \\ &\quad + \mu L\left(l_{st}, \delta^\mu\right)\left(1 - g_{st}^5\right) U_{st} + X_{st}\eta + \epsilon_{st} \ . \end{aligned} \qquad (7)$$

This is the *cohort panel data model (CPDM) for state divorce rates.* Here $X_{st} = \sum_{m=1}^5 X_{st}^m \cdot g_{st}^m$. With regard to X_{st}, we adopt the structure used by Friedberg and Wolfers, namely X_{st} is resolved into additive year fixed effects, state fixed effects, and state-specific linear and quadratic time trends. To prevent the biases noted in Bertrand, Duflo, and Mullainathan (2004), we also assume first order autocorrelation for the within-state errors (parameterized for each state as $\rho_{s.}$). The error, $\epsilon_{st} = \frac{1}{N_{st}} \sum_{i=1}^{N_{st}} \epsilon_{ist}$ is an average over all individuals in (s,t) which is heteroskedastic by construction, calling for population-based weights for the data.

Note that the second line in (7) contains a simplification of the two unilateral terms. These rely on the fact that states that adopted unilateral rights have, in fact, made no subsequent changes in their laws. Consequently, if a state adopted unilateral law, only its last or 5^{th} marriage cohort could have been married under unilateral law and the selection term in (7) simplifies to $\mu' g_{st}^5 U_s^5$. Further, the converse holds. Only couples from earlier cohorts were at risk to be surprised by the adoption of unilateral law. Thus, the surprise term in (7) simplifies to $\mu L\left(l_{st}, \delta^\mu\right)\left(1 - g_{st}^5\right) U_{st}$. [24]

If the costs of establishing grounds for divorce were observable, we would estimate (7) directly using conventional panel data methods. As they are not, the next section models costs as a continuous index which is then substituted into (7) for estimation.

[24] The algebra is $\mu^L (U_{st} \sum_{m=1}^{4} g_{st}^m - \sum_{m=1}^{4} g_{st}^m U_s^m) = \mu^L (U_{st}\left(1 - g_{st}^5\right) - \sum_{m=1}^{4} g_{st}^m \cdot 0) = \mu^L \left(1 - g_{st}^5\right) U_{st}$.

3.4 CPDM for state divorce rates - unknown costs

Inserting the cost index (2) into (7) yields the CPDM of state divorce rates. After some simplifications contained in Appendix C, the result is

$$\begin{aligned}
&d_{st} = \alpha + \beta' \left(\sum_{m=1}^{4} g_{st}^{m} \omega(w_s^m, w^*) + g_{st}^{5} \omega(w_s^5, w^*) R_{st}^{I} \right) + \beta' w_{sel}^{N} g_{st}^{5} \left[R_{st}^{II} + R_{st}^{III} \right] \\
&+ \beta L\left(l_{st}, \delta^{\beta}\right) \left(\omega(w_{st,} w^*) R_{st}^{I} - \sum_{m=1}^{4} g_{st}^{m} \omega(w_s^m, w^*) - g_{st}^{5} \omega(w_s^5, w^*) R_{st}^{I} \right) \\
&+ \beta w_{sur}^{N} L\left(l_{st}, \delta^{\beta w^N}\right) \left(1 - g_{st}^{5}\right) \left(R_{st}^{II} + R_{st}^{III}\right) + \mu' g_{st}^{5} U_{st} + \mu L\left(l_{st}, \delta^{\mu}\right) \left(1 - g_{st}^{5}\right) U_{st} + X_{st}\eta + \epsilon_{st} \ .
\end{aligned} \tag{8}$$

where, if in (s,t), the m^{th} marriage-cohort was married under R^I, the cost index is $\omega(w_{st,} w^*) = w_s^m + (w^* - w_s^m) I(w_s^m > w^*)$ as given in (1) above. Equation (8) gives the *Cohort Panel Data Model (CPDM) for state divorce rates when costs are unknown.*

In order to highlight the overidentification of the wait-time equivalent of establishing grounds for divorce and of the floodgate effects, in (8) we give different names to the parameters depending on whether they are identified by selection or surprise terms (w_{sel}^N and w_{sur}^N) as well as different names depending on whether they are identified by selection in *Regime I* or by selection in *Regimes II* or *III* (δ^{β} and $\delta^{\beta w^N}$). In Section 7.2 below we use the restrictions from the theory, namely that $w_{sel}^N = w_{sur}^N = w^N$ and that $\delta^{\beta w^N} = \delta^{\beta}$, as the basis of specification checks. Finally, we note again that if w^* were known, (8) would be linear in the (overidentified) selection, surprise, and floodgate effects $\left(\mu' \ ,\beta', \ (\beta' w_{sel}^N) \ ; \ \mu \ ,\beta, \ (\beta w_{sur}^N) \ ; \text{ and } \delta^{\mu}, \ \delta^{\beta}, \ \delta^{\beta w^N}\right)$.

For future reference, we record the special case of the CPDM with homogeneous marriage quality within cohorts where $L\left(l_{st}, \delta^{\beta}\right) = L\left(l_{st}, \delta^{\mu}\right) = L\left(l_{st}, \iota\right) = 1$.

$$\begin{aligned}
&d_{st} = \alpha + \beta' \left(\sum_{m=1}^{4} g_{st}^{m} \omega(w_s^m, w^*) + \beta' g_{st}^{5} \omega(w_s^5 w^*) R_{st}^{I} \right) + \beta' w_{sel}^{N} g_{st}^{5} \left[R_{st}^{II} + R_{st}^{III} \right] \\
&+ \beta \left(\omega(w_{st,} w^*) R_{st}^{I} - \sum_{m=1}^{4} g_{st}^{m} \omega(w_s^m, w^*) - g_{st}^{5} \omega(w_s^5, w^*) R_{st}^{I} \right) \\
&+ \beta w_{sur}^{N} \left(1 - g_{st}^{5}\right) \left(R_{st}^{II} + R_{st}^{III}\right) + \mu' g_{st}^{5} U_{st} + \mu U_{st} \left(1 - g_{st}^{5}\right) + X_{st}\eta + \epsilon_{st} \ .
\end{aligned} \tag{9}$$

With or without floodgate effects, if w^* is known, d_{st} is linear in parameters, then the CPDM is amenable to estimation via conventional panel data methods.[25] However, w^* is unknown, making the divorce rate nonlinear in w^* (and also nondifferentiable at w^*). We tackle estimation in Section 5 below. Before doing so, we first discuss the relationships between the CPDM and earlier models, including the corresponding tests of the Coase Theorem.

4 Relationships between the CPDM and earlier models

The *homogenous CPDM* nests two models. The first is a static model that depends on divorce costs and rights. The second is Friedberg (1998)'s canonical model where the effect of divorce law on divorce rates operates solely through the unilateral right to divorce.

[25] Without floodgate effects, the parameters are α, β', $\beta' w^N$, β, βw^N , μ', and μ with w^N being overidentified. With floodgate effects, there are $3(K-1)$ additional parameters, $\delta^{\beta}, w^N \delta^{\beta}$,and δ^{μ}, with δ^{β} over identified.

The first model is obtained by imposing $\mu' = \mu$ and $\beta' = \beta$ on the homogenous CPDM (9). These restrictions eliminate a fundamental insight from dynamic optimization, namely that forward looking behavior (selection into a state) is essentially distinct from reactions to surprises that occur after entry. For example, $\mu' = \mu$ reduces the expression $\mu' \cdot g^5_{st} U_{st} + \mu \cdot U_{st} \left(1 - g^5_{st}\right)$ in (9) to $\mu \cdot U_{st}$. In words, a model based in dynamic optimization (9) allocates the impact of unilateral law on divorce between a selection effect (μ', weighted by the share of the population in t that was selected into marriage under unilateral law, $g^5_{st} U_{st}$) and a surprise effect (μ, weighted by the share of the population from earlier cohorts that is surprised, $(1 - g^5_{st}) U_{st}$). In contrast, the restriction $\mu' = \mu$ forces the impact of unilateral law to be the same for all cohorts. While the algebra is a bit messier, the same story holds for the restriction reducing, $\beta' = \beta$, forcing selection and surprise effects for costs to be the same.

Together these two readily tested restrictions erase the fundamental insights from dynamic models, leaving a static model,

$$d_{st} = \alpha + \beta \left(\left\{ \left[w_{st} + \left(w^* - w_{st} \right) I \left(w_{st} > w^* \right) \right] R^I_{st} \right\} \right) + \beta w^N \left(R^{II}_{st} + R^{III}_{st} \right) + \mu R^{III}_{st} + X_{st} \eta + \epsilon_{st}, \quad (10)$$

where the divorce rate depends on contemporaneous costs and rights. This might be called a two-treatment difference-in-difference model with scaled "before" state, $\omega_{st} R^I_{st}$ and two distinct treatments, R^{II}_{st} and R^{III}_{st} (with coefficients βw^N and $\left(\beta w^N + \mu\right)$, respectively), where the scale is the cost index from (1), $\omega_{st} = w_{st} + \left(w^* - w_{st} \right) I \left(w_{st} > w^* \right)$. Unless the restrictions $\mu' = \mu$ and $\beta' = \beta$ hold, weighted least squares estimates based on (10) will be biased and inconsistent.

Imposing an additional restriction on the homogenous CPDM that eliminates the cost effects altogether, $\beta' = \beta = 0$, then

$$d_{st} = \alpha + \mu U_{st} + X_{st} \eta + \epsilon_{st} \ . \quad (11)$$

This is Friedberg's canonical *difference-in-difference model* of divorce rates for state panel data. If the restrictions $L\left(l_{st}, \delta^\beta\right) = L\left(l_{st}, \delta^\mu\right) = L\left(l_{st}, \iota\right) = 1$, $\beta' = \beta = 0$, and $\mu' = \mu$ do not all hold, then estimators based on (11) will be biased and inconsistent. We will return to these observations below in the context of testing the Coase Theorem.

Finally, we note that while dynamics are entirely absent from (10), it is still far more general than the difference-in-difference model. It might be thought of as a difference-in-difference model with three treatments $(R^I_{st}, R^{II}_{st}, R^{III}_{st})$in which one of the treatments is scaled by costs, $\omega(w_{st,} w^*) R^I_{st}$.

What models does heterogeneous CPDM nest? If we add *ad hoc* lag structures to the static model (10), we get a general model where divorce rates depend on lagged costs and lagged rights,

$$\begin{aligned} d_{st} = \alpha + \beta L\left(l_{st}, \delta^\beta\right) \left(\left\{ \left[w_{st} + \left(w^* - w_{st} \right) I \left(w_{st} > w^* \right) \right] R^I_{st} \right\} \right) \\ + \beta L\left(l_{st}, \delta^\beta\right) w^N \left(R^{II}_{st} + R^{III}_{st} \right) + \mu L\left(l_{st}, \delta^\mu\right) U_{st} + X_{st} \eta + \epsilon_{st} \ . \end{aligned} \quad (12)$$

An alternative route to specification (12) would be to start de novo with contemporaneous cost and rights terms that come into play every period regardless of marriage cohort membership. Then aggregation to the cohort level and accounting for heterogeneity and then aggregating to the state level would deliver (12). Either way, imposing $\beta = 0$ (no cost term) on (12) delivers Wolfers' model,

$$d_{st} = \alpha + \mu L\left(l_{st}, \delta\right) U_{st} + X_{st} \eta + \epsilon_{st} \ . \quad (13)$$

So are these models [(12) and thereby (13)] nested in the heterogeneous CPDM (8)? The answer is NO. To see the lack of nesting, rearrange (7) to get

$$
\begin{aligned}
d_{st} = \alpha + \left(\beta' - \beta L\left(l_{st}, \delta^{\beta}\right)\right) \sum_{m=1}^{5} g_{st}^{m} c_{s}^{m} + \beta L\left(l_{st}, \delta^{\beta}\right) c_{st} \\
+ \left(\mu' - \mu L\left(l_{st}, \delta^{\mu}\right)\right) g_{st}^{5} U_{st} + \mu L\left(l_{st}, \delta^{\mu}\right) U_{st} + X_{st}\eta + \epsilon_{st} \ .
\end{aligned} \tag{14}
$$

Then substituting out the cost index (2)shows that if and only if $\beta' = \beta L\left(l_{st}, \delta^{\beta}\right)$ and $\mu' = \mu L\left(l_{st}, \delta^{\mu}\right)$ will the heterogeneous CPDM (8) reduce to (12). But for these restrictions to hold identically for *all* lag lengths requires the trivial lag structures, $L\left(l_{st}, \delta^{\beta}\right) = L\left(l_{st}, \delta^{\mu}\right) = L\left(l_{st}, \iota\right) = 1$. That is, the restriction can hold only for the homogeneous CPDM, the cases already given in (10) and (11).

How do we interpret this lack of nesting? Perhaps the best way to think about this stems from Wolfers' insightful discussion of stock-flow dynamics in the short, medium and long run. These included immediate spikes due to "pent up demand" (captured by our μ and β), bad matches dissolving earlier than good ones (captured by our floodgate effects, ($L\left(l_{st}, \delta^{\beta}\right)$ and $L\left(l_{st}, \delta^{\mu}\right)$), and differential selection into marriage changing the nature of the "at risk" population (captured by our β' and μ')[26]. The specification (12) intermingles all of the cost-related behaviors (β', β, and δ^{β}) into one group of lags and intermingles all of the rights behaviors (μ', μ ,and δ^{μ}) into another. Wolfers' specification (13) intermingles all six into one coefficient and the associated lags. *In contrast, in the CPDM each is separately identified, preserving the crucial insight from dynamic optimization: that selection and surprise are fundamentally different.*

4.1 Unbiased Tests of the Coase Theorem

In the context of divorce, the Coase Theorem says the decision to divorce is invariant with respect to who has the right to divorce (Becker 1981) (Peters 1986) [27]. In the current context, it says that, other things equal, the same divorce rate obtains whether the right to divorce is held bilaterally by the couple or unilaterally by each spouse. The Theorem applies to already married couples and requires transferable utilities along with symmetric information and costless transfers between spouses. The alternative (with nontransferable utility, asymmetric information or costly transfers), is that under bilateral consent laws some individuals may be stuck in marriages they no longer want. Thus the adoption of a unilateral right to divorce would enable these individuals to divorce, increasing divorce rates. In terms of the CPDM, the alternative means that the contemporaneous adoption of unilateral divorce (that was not anticipated at marriage) or $(U_{st} - U_{s}^{m}) = 1$, increases divorce rates. So the hypothesis is $\mu = 0$ and the alternative, $\mu > 0$. Tests based on the CPDM (either with or without floodgate effects) automatically hold constant selection into marriage (on the basis costs or rights) as well as current costs of divorce.

Relative to the CPDM without floodgate effects, the bias of the test for $\mu = 0$ in the difference-in-difference model can be seen as arising from omitting both the selection and surprise effects of

[26] He also mentioned the equilibrium effects of more divorces thickening the remarriage market, a phenomenon to which we will return in our empirical work.

[27] Given that a couple was married, Clark (1999) assumed efficient divorce and the exhaustion of all Pareto moves. Assuming that a couples utility possibility if they remained married intersected their utility possibility frontier if they divorced, then, depending on the couple's location on each frontier, the adoption of unilateral law can actually prevent divorce. So formally, finding that the adoption of unilateral law decreases the divorce rate is consistent with efficient divorce and we can regard the direction of the effect as to be determined empirically.

costs, $\left(\beta' = \beta = 0\right)$, as well as assuming that the selection effect of unilateral law is the same as the surprise effect $\mu' = \mu$. These assumptions are counter intuitive and readily tested.

To interpret the latter restriction, we focus on the unilateral terms in the CPDM, $\mu' g_{st}^5 U_{st} + \mu \left(1 - g_{st}^5\right) U_{st}$. The first term, the selection term, weights U_{st} by the most recent cohort share (g_{st}^5), reflecting the fact that only those in this last cohort could have been selected into marriage under unilateral law. The second term, the surprise term, the weights U_{st} by the sum of the first four cohort shares $\left(\sum_{m=1}^{4} g_{st}^m = 1 - g_{st}^5\right)$, reflecting the fact that only those married prior to the adoption of unilateral law were at risk, when they married, of not anticipating the subsequent adoption of unilateral law. With $\mu' \neq \mu$, the CPDM provides for selection and surprises to have distinct effects on the divorce rate. By forcing $\mu' = \mu$, the difference-in-difference model throws out this distinction.[28], a distinction at the heart of a dynamic model of the effects of changes in the legal structure in marriage and divorce.

As noted above the so-called dynamic difference-in-difference specification is not nested in the heterogeneous CPDM. Nonetheless, the difference-in-difference specification with lags exhibits a similar, seemingly unjustified aggregation parallel to that in the homogeneous case above. For we can write the heterogeneous CPDM terms as $\mu' g_{st}^5 U_{st} + L\left(l_t, \delta^{\mu}\right) \mu \left(1 - g_{st}^5\right) U_{st}$ and the corresponding term in Wolfers' model as $L\left(l_t, \delta^{\mu}\right) \mu U_{st} = L\left(l_t, \delta^{\mu}\right) \mu g_{st}^5 U_{st} + L\left(l_t, \delta^{\mu}\right) \mu \left(1 - g_{st}^5\right) U_{st}$. The latter expression shows just how the difference-in-difference model with lags forces the effect of unilateral law on selection into marriage to be the same as the effect of the adoption of unilateral law on those married under bilateral law.[29] While this is readily tested, as emphasized in subsection above, the specification is not nested in the heterogenous CPDM.

The corresponding *natural experiment* would compare the before and after divorce rates of two states. Each state starts with the bilateral right to divorce and identical costs of divorce. Then, keeping costs the same, one state adopts unilateral law and one does not. Since the cost afterward for the adopting state is, per force, the cost of establishing no-fault grounds, w^N, then to hold it constant before and after, w^N this must also be the cost before adoption as well. That is, the key transition would be from bilateral no-fault to unilateral no-fault law. *However, no state made this transition.* Thus, even absent selection into marriage, the difference-in-difference tests of Friedberg and Wolfers, suffer from a potential bias from not holding costs constant. As costs fell when unilateral divorce was adopted, the effect of falling costs can bias up their estimates of μ.

To test the Coase theorem, we test the hypothesis that $\mu = 0$. Note that this test is different from the usual test on the coefficient on U_{st} in two regards. First, even in the simplest case with no floodgate effects, μ is the coefficient on $\left(1 - g_{st}^5\right) U_{st}$ not on U_{st}. That is, only individuals who were married before the last divorce regime were at risk of being surprised by the adoption of unilateral law. Second, other effects are held constant. As seen just below, no study prior to this one conducted an unbiased test of the Coase Theorem.

[28] This is best seen by writing the diff-in-diff term as $\mu U_{st} = \mu g_{st}^5 U_{st} + \mu \left(1 - g_{st}^5\right) U_{st}$ and comparing the coefficents on the selection and surprise terms to those of the CPDM.

[29] An additional unattractive feature is that the selection into marriage term, $L\left(\right) \mu g_{st}^5 U_{st}$, contains lags which is also counter intuitive.

5 Estimation when w^* is unknown

This section focuses on estimation of the critical wait w^* (the kink).[30] For nonlinear terms of the form in (8), Muggeo (2003) noted that the first order Taylor series expansion holds exactly at the kink. That is

$$\beta(w^* - w)I\left(w > w^*_{(r)}\right) = \beta(w^* - w)I\left(w > w^*_{(r)}\right) + \gamma I\left(w > w^*_{(r)}\right), \tag{15}$$

where as of iteration r, $w^*_{(r)}$ is a candidate value for the true value w^*. In this expression $\gamma = \beta(w^* - w^*_{(r)})$ so that γ impounds the unknown w^*.[31]. Hence, given a trial value $w^*_{(r)}$, equation (15), the terms $(w^*_{(r)} - w)I\left(w > w^*_{(r)}\right)$ and $I\left(w > w^*_{(r)}\right)$ are known and this right hand side is linear in parameters β and γ. To illustrate the technique for the simple case where y is the usual dependent variable in a least squares specification with well behaved errors, assume the model is

$$y = \alpha + \beta(w^* - w)I\left(w > w^*\right) + \epsilon = \beta(w^*_{(r)} - w)I\left(w > w^*_{(r)}\right) + \gamma I\left(w > w^*_{(r)}\right) + \epsilon. \tag{16}$$

An iterative least squares procedure is:

1. Posit an initial value, $w^I_{(0)}$. Estimate β and γ using least squares. Use these estimates, $\dot{\beta}$ and $\dot{\gamma}$, to update the proposed value of the kink point using the fact that $\frac{\dot{\gamma}}{\dot{\beta}}$ is an estimate of $(w^* - w^I_{(0)})$. Update via
$$w^*_{(1)} = w^*_{(0)} + \frac{\dot{\gamma}}{\dot{\beta}} \tag{17}$$
2. Insert this value in (16) and re-estimate to get $\ddot{\beta}$ and $\ddot{\gamma}$. Update the current estimate of w^* to $w^*_{(2)} = w^*_{(1)} + \frac{\ddot{\gamma}}{\ddot{\beta}}$, and so on.

After each iteration re-estimate (16) using $w^*_{(r+1)} = w^*_{(r)} + \frac{\widehat{\gamma}}{\widehat{\beta}}$, where the estimates $\widehat{\gamma}$ and $\widehat{\beta}$ are taken from the most recent iteration. The procedure continues until the differences in successive estimates of w^* are sufficiently small to make no practical difference. Muggeo showed that, although convergence is not guaranteed, if convergence is achieved, the procedure yields maximum likelihood estimators for all of the parameters. The estimated standard deviation for the final estimate, $\widehat{w}^I_*$, can be calculated by the delta method.

Making two such approximations in 8 yields the specification to be estimated,

[30] We can also used a grid search on w^I_*. This would require jackknifed standard errors.

[31] Intuitively, for a proposed value for the kink, $w^*_{(r)}$, the parameter γ is the vertical gap between the line segment with slope β to the left of $w^*_{(r)}$ and the line of constant height to the right. As these lines should intersect at exactly at w^*, the updating equation (17) adjusts the parameter estimates to reduce the size of this gap. If convergence obtains, the estimated γ should be very small and insignificant.

$$
\begin{aligned}
d_{st} = \alpha + \beta' & \left\{ \sum_{m=1}^{4} g_{st}^{m} [w_s^m + (w_{(r)}^* - w_s^m) I\left(w_s^m > w_{(r)}^*\right)] + g_{st}^5 [w_s^5 + (w_{(r)}^* - w_s^m) I\left(w_s^5 > w_{(r)}^*\right)] R_{st}^I \right\} \\
& + \gamma' \left\{ \sum_{m=1}^{4} g_{st}^{m}\, I(w_s^m > w_{(r)}^*) + g_{st}^5\, I(w_s^5 > w_{(r)}^*) R_{st}^I \right\} + \beta' w^N \cdot g_{st}^5 \left(R_{st}^{II} + R_{st}^{III}\right) \\
& + \beta L\left(l_{st}, \delta^{\beta}\right) \cdot \Bigg\{ [w_{st} + (w_{(r)}^* - w_{st}) I\left(w_{st} > w_{(r)}^*\right)] \\
& \qquad - \sum_{m=1}^{4} g_{st}^{m} [w_s^m + (w_{(r)}^* - w_s^m) I\left(w_s^m > w_{(r)}^*\right)] - g_{st}^5 [w_s^5 + (w_{(r)}^* - w_s^m) I\left(w_s^5 > w_{(r)}^*\right)] R_{st}^I \Bigg\} \\
& + \gamma \left\{ I\left(w_{st} > w_{(r)}^*\right) - \sum_{m=1}^{4} g_{st}^{m}\, I(w_s^m > w_{(r)}^*) - g_{st}^5\, I(w_s^5 > w_{(r)}^*) R_{st}^I \right\} \\
& + \beta w^N L\left(l_{st}, \delta^{\beta w^N}\right) \left(1 - g_{st}^5\right) \left(R_{st}^{II} + R_{st}^{III}\right) + \mu' g_{st}^5 U_{st} + \mu^N L\left(l_{st}, \delta^{\mu}\right) U_{st} \left(1 - g_{st}^5\right) + X_{st}\eta + \epsilon_{st} \ ,
\end{aligned}
\tag{18}
$$

Here γ' and γ emerge from two approximations, one for selection and the other for surprise terms. For the r^{th} iteration and a given candidate value $w_{(r)}^*$, equation (18) is a linear function of the eight parameters, $\gamma', \gamma, \beta', \beta, (\beta' w^N), \left(\beta w^N\right), \mu'$ and μ. The estimates of $\gamma'$and γ will in general imply different updates for w^*. If both are estimated with precision, this can handled by using a precisioon weighted average of the two or by alternately updating each candidate value. In practice we have found that given a difference in precision, weighting the the more precise update (γ in our case) with one and the other with zero can lead to rapid convergence and the desired estimates.

To summarize, we imbed this iterative procedure into standard panel data methods. Each iteration is then a conventional root population weighted GLS regression that includes within-state first order autocorrelated errors as well as year effects, state fixed effects and linear and quadratic state-specific time trends.

6 State panel data

We used three types of state panel data, divorce rates, divorce laws, and marriage-cohort shares

6.1 Divorce rates.

Along with many other studies, this one has benefited from the construction and sharing of data, especially the work of Friedberg (1998), Wolfers (2006), and Gold (2008). From Vital Statistics on all divorces, Friedberg compiled a panel of state divorce rates from 1968-1998. Using data from law journals, she also compiled and published divorce laws for this interval, including grounds for divorce, including minimum separation periods (wait times). She generously shared these data with Wolfers for his study. He, in turn, extended these data back to 1956 and posted all of these data on his website. Our data on divorce rates comes from his website.

6.2 Divorce laws

For all states plus the District of Columbia, the following table contains the relevant changes in divorce laws since 1850. The first four columns contain the coding used in this study, the next four columns contain Gold's coding of these laws, and the last two columns contain the coding of unilateral law used by Friedberg and by Wolfers, respectively.

For our coding, the first two columns describe wait times (i.e., minimum number of years living separate and apart). The first column gives the minimum time in years; the second column documents the year that this minimum was implemented. With regard to timing, a law is coded as effective as of t if the date that that law became effective falls between July 1 of year $t-1$ and June 30 of year t.

If a state ever implemented no-fault grounds, the third column lists the year it was first implemented. In these laws the usual language for no-fault grounds include one of the following: "Incompatibility," "Irreconcilable differences," or "Irretrievable breakdown" of the marriage; hence the column header is III. In addition to no-fault grounds, a large number of states went farther than just implementing no-fault grounds. This subset of states, in the same bills in which they adopted no-fault grounds also specified that either spouse could file for and obtain a divorce on no-fault grounds without the consent of the other. We classified these states as having unilateral law. Thus no-fault grounds are a necessary condition for unilateral law, but not sufficient. The year in which a state implemented unilateral rights is recorded in the fourth column (header is Unilateral). While in principle states might have adopted no-fault grounds in one year and gone on to adopt the unilateral right in a subsequent year, in fact no state did this; see Section 2.5. Thus, if there is a year given in the Unilateral column, the same year is given in column III.

As examples, consider Louisiana, South Dakota, and Nevada. As shown in the first two columns, Louisiana, implemented a minimum wait time of 7 years in 1916. The required period was then reduced to 4 years in 1932, to 2 years in 1938, to 1 year in 1979, and to 0.5 years in 1991. The blank spaces in the third and fourth columns (III + Unilateral) indicate that no-fault ground were never implemented by Louisiana. In contrast, South Dakota never included living separate and apart as an admissible ground, but instituted no-fault grounds in 1985. The blank space in the (+Unilateral) column indicates that South Dakota never implemented a unilateral right to divorce. A more liberal example is Nevada. The first two columns show that prior to 1931 Nevada was a bilateral fault state. As of 1931 Nevada instituted a required separation period of 5 years, reducing it to 3 years in 1939 and 1 year in 1967. No-fault grounds were also instituted in 1967 as shown in the (III) column (3). Column (+Unilateral) further specifies that also as of 1967, Nevada allowed a petition to divorce based on no-fault grounds to be granted to either spouse without the consent of the other.

The next four columns document divorce law in Gold (2008) in a similar fashion. As noted above, the last two columns summarize the years used in Wolfers (2006) and Friedberg (1998). Among these three sources, Gold (2008) is the most comprehensive. For each state he identifies each bill (giving the year and the chapter number or the house bill number, the approval date (down to the day) and, if known, the effective date (down to the day). This greatly eases the burden of finding the laws themselves as well as relevant interpretations in state courts..Sources of discrepancies in coding amongst the four studies are discussed in Appendix D.

Our classification of states is detailed in the Table that follows.

6.3 Marriage cohort shares

Our third piece of data is the marriage cohort shares. Apart from Decennial Census years, there seem to be no state panel data on the stock of married women in (s,t), much less on married cohort

State	Separation		This paper		Gold		Gold		Wolfers	Friedberg
	(1) Length	(2) Year	(3) III	(4) + Unilateral	(5) III	(6) + Unilateral	(7) Separation	(8) + Unilateral	(9) Unilateral	(10) Unilateral
Alabama	5	1915	1972	1972	1972	1972	1972	1972	1971	1971
	2	1947								
Alaska			1935	1935	1963	1963			1935	pre-1968
Arizona	5	1931	1974	1974	1974	1974			1973	1973
Arkansas	3	1937					1937	1937		
	1.5	1991								
California			1970	1970	1970	1970			1970	1970
Colorado			1972	1972	1972	1972			1971	1971
Connecticut	1.5	1973	1973	1973	1973	1973	1973	1973	1973	1973
Delaware	3	1957	1975		1975		1957			
	1.5	1968								
DC	5	1935					1966			
	1	1966								
Florida			1972	1972	1972	1972			1971	1971
Georgia			1973	1973	1973	1973			1973	1973
Hawaii	3	1967	1974	1974	1974	1974	1965		1973	1973
	2	1970								
Idaho	5	1945	1971	1971	1971	1971			1971	1971
Illinois	2	1984					1984	1984		1984
Indiana			1974	1974	1974	1974			1973	1973
Iowa			1971	1971	1971	1971			1970	1970
Kansas			1970	1970	1970	1970			1969	1969
Kentucky	5	1850	1972	1972	1972	1972			1972	1972
Louisiana	7	1916					1961	1961		pre-1968
	4	1932								
	2	1938								
	1	1979								
	0.5	1991								
Maine			1974	1974	1974	1974			1973	1973
Maryland	5	1937					1937	1937		pre-1968
	3	1947								
	1.5	1961								
	1	1983								
Massachusetts			1976	1976	1976	1976			1975	1975
Michigan			1972	1972	1972	1972			1972	1972
Minnesota	5	1935	1974	1974	1974	1974	1935	1935	1974	1974
	1	1974								
Mississippi			1977		1977					
Missouri			1974	1974	1974	1974				
Montana	0.5	1976	1976	1976	1976	1976			1975	1975
Nebraska			1972	1972	1972	1972			1972	1972
Nevada	5	1931	1967	1967	1967	1967	1931	1931	1973	1973
	3	1939								
	1	1967								
New Hamshire	3	1938	1972	1972	1972	1972	1957	1957	1971	1971
	2	1957								
New Jersey	1.5	1972	2007		1972	1972				1971

State	Separation		This paper		Gold		Gold		Wolfers	Friedberg
	(1) Length	(2) Year	(3) III	(4) + Unilateral	(5) III	(6) + Unilateral	(7) Separation	(8) + Unilateral	(9) Unilateral	(10) Unilateral
New Mexico			1933	1933	1933	1933			1973	1973
New York	1	1968					1968			
North Carolina	10	1907					1931	1931		
	5	1921								
	2	1933								
	1	1965								
North Dakota			1971	1971	1971	1971			1971	1971
Ohio	2	1975	1990		1990		1975	1975		1974
	1	1982								
Oklahoma			1953	1953	1953	1953			1953	pre-1968
Oregon			1972	1972	1972	1972			1973	1973
Pennsylvania	2	1988	1981		1981					1980
Rhode Island	10	1893	1975	1975	1975	1975			1976	1976
	3	1975								
South Carolina	3	1969					1969	1969		1969
	1	1979								
South Dakota			1985		1985				1985	1985
Tennessee	2	1977	1977		1977		1977	1977		
Texas	10	1925	1970	1970	1970	1970	1953		1974	1974
	7	1953								
	3	1967								
Utah	3	1965	1987	1987	1987	1987	1943	1943		pre-1968
Vermont	3	1941					1941	1941		pre-1968
	2	1971								
	0.5	1972								
Virginia	3	1960					1960	1960		pre-1968
	2	1964								
	1	1975								
Washington	8	1917	1973	1973	1973	1973			1973	1973
	5	1921								
	2	1965								
West Virginia	2	1969	1978	1978	1978	1978	1969	1969		pre-1968
Wisconsin	5	1866	1978		1978		1978	1978		1977
	1	1978								
Wyoming	2	1939	1977	1977	1977	1977			1977	1977

Table 2: Divorce laws in the United States, 1850-1995. The length of the separation requirement is in years. Souces of separation requirement are Difonzo (1997) and Vlosky and Monroe (2002). The III ground refers to divorce ground that includes such terms as incompatability, irreconcilable difference, and irretrievable breakdown where a mutual consent is required. The column with + Unilateral refers to the year in which no mutual consent is required to file a divorce based on the ground in the preceding column. The year used in our analysis and Gold's is rounded up to the next year if the divorce law is effective after June of that year. The year used in Wolfers and Friedberg is based on the calendar year. The definition of the no-fault year in Gold is the minimum of the III year and separation year.

shares.[32] We construct a proxy from the CPS. The proxy is based on the annual age distribution of women in each state from the CPS in relation to the national median age at first marriage. For each state, these are normed on the same ratio as of the year before that state first changed its divorce laws. The resulting proxies behave in ways that conform to expectations. Limitations of the CPS preclude the construction of cohort shares for years prior to 1962. Hence, for the specifications below that include cohort shares, the sample period is shortened to 1962-1988.

The idea is as follows. The key is to measure for each state and a given change in its divorce law, the fraction of women married in t who were married before the last change in the law. Focus on one state and drop the subscript s and, to be concrete, suppose a new law came into effect in 1970. Let t be any year before or after 1970. And let Υ_{70} be the median age of first marriage in 1970. Define W as the stock of women in t who, as of 1970, were older than Υ_{70}. Define M_t as the stock of married women in t. Assume that that $M_t = kW_t$ and that k does not vary with time. We seek the stock of women in t who were married before 1970 as a fraction of all married women in t. That is, we seek $P_t = \frac{kW_t}{M_t}$. Now all married women in 1969 were married before the new law came into effect in 1970 so that $P_{69} = \frac{kW_{69}}{M_{69}} = 1$. Thus $k = \left(\frac{W_{69}}{M_{69}}\right)^{-1}$. Substituting, $P_t = \left(\frac{W_{69}}{M_{69}}\right)^{-1} \frac{W_t}{M_t}$.

Hence, if state s only changed its laws once, in 1970, in our sample period, then, adding in the state subscript, the stock of women in t who were married before 1970 as a fraction of all married women in t is $g^1_{st} = P^{70}_{st}$. The remaining married women in t married after 1970. So there share is $g^5_{st} = 1 - P^{70}_{st}$. More generally, if a state changed its laws twice in our sample period, say in τ_1 and in τ_2, then,

$$\begin{aligned} g^1_{st} &= P^{\tau_1}_{st}, \text{ for all } t \\ g^2_{st} &= \begin{cases} 1 - P^{\tau_1}_{st}, \text{ if } t < 1975 \\ P^{\tau_2}_{st} - P^{\tau_1}_{st}, \text{ if } t \geq 1975 \end{cases} \\ g^5_{st} &= 1 - P^{\tau_2}_{st} \text{ for all } t\ . \end{aligned} \tag{19}$$

These definitions readily generalize to our required five cohort shares.

7 The estimated CPDM

Before presenting estimates of the CPDM, we first check the specification of the cost index and its robustness.

7.1 The Cost Index

Recall that the cost index (2) of establishing grounds for divorce measures the cost of divorce in terms of utility-equivalent wait times. It applies to all regimes and to all combinations of costs and rights in our data. In particular as shown in Section 2.3 above, under bilateral fault law the absence of a wait time produces the same behavior as would a "long" wait, where long means longer that w^*, namely couples who divorce go to court and "prove" fault at a cost proportional to w^*. Key

[32] We did attempt to construct the actual shares, benchmarked by Census Years. For a year following the Censu year we added in new marriages and subtractied out divorces, and so on. This, however, proved fruitless as too many additions and subtractions are unknown (e.g. interstate migrations by marital status, deaths by marital status, and so forth). We concluded, all and all that these constructed proportions compared unfavorably with simple interpolations between Censu years.

Specification:	(1)	(2)	(3)	(4)
If no w, then w assigned:	8 yrs.	10 yrs.	8 yrs.	8 yrs.
Sample period:	1956 − 88	1956 − 88	1962 − 88	1956 − 88
				$(\beta_1+\beta_2)=0$
α	3.5616***	3.5616***	3.6253***	3.5532***
	(0.1239)†	(0.1239)	(0.1349)	(0.1170)
β_1	−0.2148***	−0.2148***	−0.2287***	−0.2135***
	(0.0588)	(0.0588)	(0.0632)	(0.0578)
β_2	0.2107***	0.2119***	0.2241***	*
	(0.0578)	(0.0579)	(0.0621)	*
γ	6.3×10^{-7}	1.7×10^{-5}	8.12×10^{-7}	5.72×10^{-8}
	(0.0672)	(0.0652)	(0.0771)	(0.0501)
w^*	2.0499***	2.0551***	2.0946***	2.1349***
	(0.3127)	(0.303)	(0.3372)	(0.2345)
w^N	1.2191***	1.2191***	1.4784***	1.1875***
	(0.3966)	(0.3966)	(0.3410)	(0.3829)
μ	−0.0672	−0.0672	−0.0565	−0.0707
	(0.0734)	(0.0734)	(0.0680)	(0.0732)
χ^2 for	0.13	0.13	0.15	*
$\beta_1+\beta_2=0$	[0.7136]	[0.7136]	[0.6967]	
N	1631	1631	1343	1631
χ^2	40105.65	40105.65	43902.30	40232.56
	[0.0000]‡	[0.0000]	[0.0000]	[0.0000]

Estimates from population-weighted GLS regressions including state and year FE's, linear and quadradic state-specific time trends and first order autocorrelated errors within-states.

† Asymptotic standard errors in parentheses.

(*,**,***) indicate 'significance' at the (.10, .05, and .01) levels, respectively.

‡ $p-$values in brackets. ✓ indicates the hypothesis is maintained. Tx.

Table 3: Static model using kinked cost index

features of the cost function that manifest themselves in the state divorce rate are (i) a kink at w^* (the wait-time equivalent of the cost of a sham trial to "prove" fault), (ii) a decreasing divorce rate to the left of w^*, (iii) a zero slope to the right of w^*, and (iv) a cost of establishing no-fault grounds (w^N) that is less than w^*. In this section we show that these features are robust with respect to the choice of a "long" wait time for bilateral fault states that had no wait times, with respect to truncating the sample period,[33] and with respect to the imposition of a zero slope to the right of the kink.

Table 3 reports the corresponding specification checks. Based on the simple generalization of the static model (10),[34] β_1 is the slope to the left of w^* and $(\beta_1+\beta_2)$ is the slope to the right. As

[33] Recall that due to limitations of the CPS, we must truncate our sample from Wolfers' 1956-1988 to 1962-1988.

[34] As for all of our estimates, we weight each observation by the time-varying root of the state population. We follow Friedberg's specification for coping with unobserved covariates (the X's) with state and year fixed effects as well as

shown in the column headers, the specifications vary by the "long" waiting time assumed when no wait time was available (10 years in column (2) vs. 8 years in the rest), the sample period (beginning with 1962 in column (3) vs. 1956 in the rest) and the imposition of the restriction $(\beta_1 + \beta_2) = 0$ (column (4) vs. the rest).[35] For all four specifications, convergence was strong as indicated by small (i.e., orders of magnitude smaller than any other estimated coefficient) and insignificant estimates for γ.[36] In contrast, with the exception of μ the remaining coefficients are all significant at the .01 level.

Looking across the rows of Table 3, the parameter estimates are remarkably robust across all four specifications. The pattern that emerges in every case is (i) the estimate of the kink, w^* is about 2.1 years; (ii) the slope to the left of w^* is negative and about -0.21 divorces per thousand people; (iii) the estimate of β_2 is about .21 so that the estimated slope to the right of w^*, namely $(\beta_1 + \beta_2)$, is very close to zero (a point corroborated by the the corresponding asymptotic χ^2 tests toward the bottom of the table); and (iv) w^N is about 1.3 years and less than w^* as required by the theory.

In sum, the cost index parameters are in line with the theory and quite stable across all of these specifications. In particular, there is strong evidence that to the right of the estimated kink the slope of the cost function is zero. Hence, in estimating the full CPDM we impose this restriction. In addition, we assign a "long" wait of $w = 8$ years to bilateral fault states in years in which they had no alternative wait time to establish grounds for divorce.

7.2 The estimated CPDM

Table 4 displays maximum likelihood estimates for six specifications of the CPDM, all using our adaptation of Muggeo's iterative procedure (18).

The specification checks take advantage of the overidentification of the floodgate effects resulting from cost surprises (δ^{β}) as highlighted in (8) above. With regard to floodgate effects, there are three treatments. In the first two columns $\delta^{\beta w^N}$ and δ^{β} are free to be different; in the middle two columns, $\delta^{\beta w^N} = \delta^{\beta}$ in accordance with the theory; and in the last two columns floodgate effects are eliminated altogether $(\delta^{\beta w^N} = \delta^{\beta} = \iota$, a vector of ones) as per the homogeneous CPDM (9). Estimates of the floodgate parameters per se are relegated to Appendix B.

For each parameter looking across the corresponding row reveals remarkably consistent estimates across all six specifications. First, estimates of two parameters are essentially zero, namely those for selection into marriage on the basis of rights μ' (the smallest p-value is .58) and the responses to the surprise adoption of unilateral law μ (the smallest p-value is .28). In addition, the corresponding floodgate effects are absent as we cannot reject $\delta^{\mu} = \iota$ (the p-values are .89 and .87). Hence, in columns (2),(4) and (6) we impose these three restrictions.

Taken together, that μ' and μ are both insignificantly different from zero and that δ^{μ} is insignificantly different from ι (a vector of ones) constitute strong evidence for the Coase Theorem. Recall that only if divorce decisions are inefficient will violations of the theorem be found. In that case

linear and quadratic state-specific time trends. In addition we allow for 51 state-specific first order autocorrelations.

[35] The first column of Table 5 can be regarded as yet another specification check on the parameters of the cost index.

[36] The convergence criterion for the estimates in the table is 0.0001. Similar results are found when the lack of a wait time is interpreted as $w = 5, 6$,and 7, but with the convergence criterion was 0.01. In general, the closer to the kink these long waits are assumed to be, the slower the convergence.

		CPDM Extra Floodgate Effects $\delta^{\mu}, \delta^{\beta}, \delta^{\beta w^N}$ free		**CPDM** Exact Floodgate Effects $\delta^{\mu}, \delta^{\beta}$ free $\delta^{\beta w^N} = \delta^{\beta}$		**CPDM** No Floodgate Effects $\delta^{\mu} = \delta^{\beta} = \delta^{\beta w^N} = 0$	
		(1)	(2)	(3)	(4)	(5)	(6)
	α	4.430*** (1.105)†	4.483*** (1.117)	4.237*** (1.001)	5.049*** (0.957)	4.817*** (1.033)	4.872*** (1.023)
SELECTION	μ'	−0.401 (1.151)	0	−0.321 (1.135)	0	−0.616 (1.097)	0
	β'	−0.615 (0.513)	−0.641 (0.523)	−0.524 (0.464)	−0.804** (0.396)	−0.804* (0.488)	−0.822* (0.479)
	w^N_{sel}	1.117 (1.989)	1.724*** (0.604)	1.087 (2.260)	2.113*** (0.423)	1.223 (1.401)	1.941*** (0.389)
SURPRISE	μ	−0.075 (0.071)	0	−0.077 (0.071)	0	−0.064 (0.069)	0
	β	−0.239*** (0.064)	−0.244*** (0.064)	−0.237*** (0.062)	−0.115** (0.051)	−0.230*** (0.061)	−0.228*** (0.061)
	w^N_{sur}	1.394*** (0.327)	1.652*** (0.204)	1.371** (2.56)	1.285 (0.820)	1.379*** (0.326)	1.587*** (0.218)
	w^*_{sur}	2.149*** (0.217)	2.134*** (0.209)	2.151*** (0.219)	2.406*** (0.505)	2.114*** (0.221)	2.133*** (0.224)
	γ	$1.44x10^{-8}$ (0.052)	$2.35x10^{-8}$ (0.051)	$-4.02x10^{-9}$ (0.052)	$8.38x10^{-9}$ (0.058)	$1.98x10^{-8}$ (0.051)	$-1.67x10^{-8}$ (0.051)
TESTS	$\delta^{\mu} = \iota$	[0.885]‡	✓	[0.869]	✓	✓	✓
	$\delta^{\beta} = \iota$	[0.658]	[0.636]	[0.024]	[0.094]	✓	✓
	$\delta^{\beta w^N} = \delta^{\beta}$	[0.964]	[0.302]	✓	✓	✓	✓
	χ^2_{df}	48,529.17	48,449.46	47,660.66	47,846.49	44,626.97	44,752.36
	df	195	189	191	185	183	181

NOTES

N=1343. All estimates from population-weighted GLS regressions, within-state first-order autocorrelated errors, state and year FE's, and state-specific linear and quadratic time trends.
† Asymptotic standard errors in parentheses.
(*,**,***) indicate 'significance' at the (.10, .05, and .01) levels, respectively.
‡ p−values ✓ indicates the hypothesis is maintained. Tx.

Table 4: Estimated Divorce Equations, Cohort Panel Data Model

one would find that the surprise adoption of unilateral law would allow those stuck in marriages they no longer want to divorce, $\mu > 0$. Hence the divorce rate for those already married would spike immediately ($\mu > 0$) and unobserved hetereogeneous match quality would lead to this effect tapering off with the passage of time (declining elements of δ^{μ} or floodgate effects). Further, cohorts selected into marriage under unilateral law would have better marginal marriages than others (better enough to offset the risk of being deserted by a potential spouse) and thereby lower divorce rates ($\mu' < 0$). To reiterate, as we cannot reject any one of this cluster of restrictions implied by the Coase Theorem ($\mu' = 0$, $\mu = 0$, and $\delta^{\mu} = \iota$); our results strongly support the Theorem.

Thus our results tell a story of entry and exit from marriage that is influenced not by who has the right to file for divorce but by the costs of establishing grounds for divorce. As seen in Table 4, in conformance with the theory, all six specifications yield the effect of a surprise change in the cost of divorce β to be negative and statistically significant. Five of these six estimates are in a narrow range, $-.23$ to $-.24$ and the remaining estimate is $-.12$. As shown by the p-values for tests of the absence of floodgate effects ($\delta^{\mu} = \iota$ and $\delta^{\beta} = \iota$), floodgate effects proved significantly different from a vector of ones, only under the restriction, $\delta^{\beta w^N} = \delta^{\beta}$, that is in columns (3) and (4). In addition, once we impose the Coase restrictions (column (4) in Table 4) with one exception, the estimated floodgate effects,[37] follow the predicted pattern of decline as the the surprise recedes into the past. The exception is an uptick at the end. The effect for a surprise 13 or more years ago is somewhat larger than one for 10-12 years years ago. This is likely due to an effect that remains outside our model, namely the thickening of the remarriage market that attended the surge in divorce rates in the 1970's and the continuation of higher rates thereafter.[38] We sum up with the numerical implications. For our smallest (in absolute value) estimate of β of $-.12$, an unanticipated drop in the cost index of one year would result in a spike in the divorce rate of .12 divorces per 1,000 population ($\beta \cdot \Delta w \cong (-0.12) \cdot (-1)$) followed by a decline for up to 10-12 years after the surprise and than a small permanent uptick which we attribute to thickening of the remarriage market.

With regard to selection into marriage on the basis of costs, our estimates have the appropriate signs but attain conventional significance only when some restrictions are maintained [either $\delta^{\beta w^N} = \delta^{\beta}$ and the Coase restrictions as in column (4) or else the restriction of no floodgate effects, $\delta^{\beta w^N} = \delta^{\beta} = \iota$ as in columns (5) and (6)]. The significant estimates are all close to $-.81$, indicating that, a younger cohort married under laws with a cost index that was one year shorter than an older cohort would have a divorce rate that is higher by .81 divorces per thousand people than the older cohort. As the difference for the national rates between 1962 and the peak rate is about three divorces per thousand, such a one year decrease would explain about 27% of the steep increase in the divorce rate from 1962 through the end of the 1970's. Further, if we took the permanent increase in the US divorce rate to be the most recent one in our data or about 3.5 divorces per thousand, then this selection effect of a one year reduction in the cost index would explain over half ($\frac{.81}{1.4}$) of the permanent increase.

Turning to the estimated cost parameters, (with p-values all less than .01) all six specifications

37 Estimates of these floodgate parameters can be found in column (4) of Appendix B Table 6.

38 With regard to tests for floodgate effects per se, toward the bottom of Table 4 are prob-values for tests of the hypothesis of no floodgate effects ($\delta^{\mu} = \iota$ and $\delta^{\beta} = \iota$). Since our estimates all indicate that $\mu = 0$, it is no surprise to find evidence for a lack of floodgate effects associated with the adoption of unilateral law (prob- values in excess of .86). When the floodgate effects associated with cost surprises are overspecified as in columns (1) and (2), we also cannot reject the absence of the corresponding floodgate effects (both p-values exceed.30). But once we get rid of the overspecification by imposing the restriction dictated by theory ($\delta^{\beta w^N} = \delta^{\beta}$) as in columns (3) and (4), then we reject the absence of floodgate effects (with p-values of .024 and .094).

deliver precise estimates of the cost of proving "fault" w^* that lie in a relatively narrow range from 2.1 to 2.3 years, highly plausible values. As pointed out in section 3.4 above, the parameter for the cost of establishing no-fault grounds, w^N, is overidentified and thus each of the six specifications in Table 4 contains two estimates, w^N_{sel} identified off of the cost selection terms, and w^N_{sur} identified off of the cost surprise term. Correspondingly, despite conforming to the theory (negative and less than w^*), these 12 estimates of w^N_{sur} have a disquietingly wide range from 1.11 to 2.11 years. Because the estimated effects of costs surprises (β) are more precise than those for selection on costs(β'),[39] and because the specifications (3) and (4) adhere most closely to our theory, we prefer the estimates of w^N_{sur}.under these specifications, roughly 1.3 years, also a very plausible value.

All in all, the specifications dictated by the theory, those for columns (3) and (4) seem to contain the best estimates of the CPDM for state panel data on divorce rates. And between these two, it seems that imposing the cluster of Coasian restrictions as in column (4) likely gives the best estimates. In this column all of the estimates in Table 4 all conform to the theory as do, with one exception, the corresponding floodgate effects in Appendix B, Table 6.[40]

7.3 Estimates of nested and related models

Table 5 reports estimates for the four models corresponding to equations (10), (11), (12), and (13) in Section 4 above. Here the subscript "S" (for same) is used to distinguish the parameters of these models from those of the CPDM. Equation (12) is the static model nested in the CPDM obtained by imposing $\mu' = \mu = \mu_S$ and $\beta' = \beta = \beta_S$ on the CPDM. Imposing in addition $\beta_S = 0$ yields Friedberg's specification (11). The third column contains a dynamic generalization of (10), namely equation (12), obtained by specifying a Wolfers-like lag structure for costs as well as rights (for β as well for μ). This generalization obviously nests (13), the specification used by Wolfers which may be obtained by excluding all cost effects. Estimates of the lag parameters for (12) and (13) are given in Table 7 in Appendix B.

Our estimates with no costs terms in columns (11) and (13) give results similar to Friedberg and Wolfers[41] At first blush the positive and significant estimates of μ_S indicate that contemporaneous unilateral laws increased divorce rates. Note, however, that when the corresponding cost variables are added to their specifications as in columns (10) and (12), the estimates of μ_S become insignificant and negative. At the same time parameters of the cost index, β_S, w^N_S, and w^*_S emerge as significant with appropriate signs, and sizes. Thus, even if one accepts a static framework (that the impact of divorce law changes are uniform across all marriage cohorts) it appears that the positive and significant estimates of μ_s found by Friedberg and by Wolfers suffered from bias due to the omission of costs. Put otherwise, their results should not be construed as evidence against the Coase Theorem.

Finally, columns (12) and (13) further illuminate Wolfers' results. Both include nonparametric lags on how long unilateral law has been in effect (δ^μ). Column (12) also hits the cost effect (β)

[39] For each of the six specifications the p-value of the estimated β was less than the p-value for the estimated β'.

[40] As explained earlier, the last estimated coefficent in the δ^β vector is higher than the previous one. While this last uptick does not conform with the theory, it is likely explained by thickening remarriage markets as more divorced persons became avaiable for remarriage.

[41] While qualitatively similar, our estimates in columns (11) and (13) differ somewhat from theirs for several reasons. Our sample period begins in 1962 whereas Friedberg's begins in 1968 and Wolfers' in 1956. Our classification of which states are unilateral differs somewhat from theirs; see Section 6. In addition we allow for within-state first order autocorrelated errors.

Specification:	(10) Friedberg + costs	(11) Friedberg	(12) Wolfers + costs	(13) Wolfers
α	3.602*** (0.128)†	3.118*** (0.056)	3.594*** (0.146)	3.101*** (0.058)
μ_S	−0.067 (0.068)	0.096*** (0.035)	−0.079 (0.071)	0.090*** (0.036)
β_S	−0.225*** (0.062)		−0.227*** (0.072)	
w_S^N	1.379*** (0.334)		1.310*** (0.353)	
w_S^*	2.152*** (0.230)		2.150*** (0.229)	
γ_S	$1.28x10^{-8}$ (0.052)		$2.15x10^{-8}$ (0.052)	
Tests of				
$\delta^\mu = \iota$	✓	✓	[0.863]‡	[0.615]
$\delta^\beta = \iota$	✓		[0.914]	

N=1343. Estimates from population-weighted GLS regressions with first order autocorrelated errors within states, state and year FE's, and linear and quadratic state-specific time trends.
† Asymptotic standard errors in parentheses.
(*,**,***) indicate 'significance' at the (.10, .05, and .01) levels, respectively.
‡ $p-$values. ✓ indicates the hypothesis is maintained. Tx.

Table 5: Estimated divorce rates for specifications (10), (11), (12) and (13)

with analogous nonparametric lags, $L(l_{st}, \delta^{\beta})$. In neither of these specifications are the sets of lags δ^{μ} jointly significant nor is the set of lags δ^{β} in (12) jointly significant.

An interesting phenomenon arises if, contrary to the results reported in Table 5 and 7 we repeat the estimation assuming no within state autocorrelations for the errors. This brings us one step closer to Wolfers' actual specification. In results not shown in this paper, without autocorrelated errors, estimates of (13) yield lag parameters δ^{μ_S} that are jointly significant (reject $\delta^{\mu_S} = \iota$ with prob- value of .07). However, once cost parameters β_S, w_S^N, and w_S^* are included with their associated lag structure $L(l_{st}, \delta^{\beta_S})$ as in (12), neither lags on costs nor lags on rights remain significant; tests of $\delta^{\beta} = \iota$ and $\delta^{\mu} = \iota$ yield prob-values upwards of 0.75. Thus, it appears that in Wolfers, the estimated nonparametric lags, δ^{μ_S} owed their significance to the omission of costs and the absence of an allowance for within state autocorrelations.

8 Conclusions

We present a new approach to the estimation of dynamic models using panel data, not on individuals, but aggregated to some level such as the school, county or state. This approach embeds the reduced form implications of dynamic optimization for exiting a chosen state (via divorce, dropping out, employment, etc.) into a model suitable for estimation with state panel data or similar aggregates (school, county, SMSA, etc.). With forward looking behaviors, exogenous changes in laws or rules give rise to selection effects on those considering entry and surprise effects for those who have already chosen to enter. Key to the resulting cohort panel data model (CPDM) is tracking the differential selection embodied in entry cohorts as well as accounting for within-cohort unobserved heterogeneity in response to surprises with floodgate effects.

Our application is to the effects of divorce laws on divorce rates. At the individual level, responses to changes in the law are captured by selection effects and surprise effects for both costs and rights. For congruence with the theory we recode the divorce law data and postulate a continuous index of the cost of divorce that maps grounds for divorce into an index of the total cost of divorce. We find strong evidence for the cluster of predictions of the Coase Theorem: with regard to the right to divorce we find (i) no evidence that cohorts select into marriage based on unilateral law, (ii) no evidence that the unanticipated adoption of unilateral law increases the divorce rates of those already married, and (iii) no evidence for associated floodgate effects. With regard to the cost of divorce, we find that the surprise lowering of divorce costs increases divorce rates in the short run, and that lowering divorce costs also decreases the quality of the marginal marriage and thereby increases the divorce rate in the long run. We show that earlier tests of the Coase Theorem suffer from omitted variable biases and inappropriate aggregation.

Studies that purported to find the effect of unilateral laws on child well being, crime and other social ills are likely finding the effect of somewhat missmeasured reductions in divorce costs. After all, the adoption of unilateral law was always accompanied by a lowering of divorce costs (though the reverse is not true). It appears that these studies would get stronger results by using a measure of costs such as our cost index in place of unilateral law.

Every state legislated some form of low-cost divorce law by (I) adopting short wait times, (II) adopting no-fault grounds for divorce or (III) adopting no-fault grounds and a unilateral right to divorce. Recall that Figure 3 shows the divorce rates along these three paths. Paths I and II nearly lie on top of each other. Furthermore, the *changes* in divorce rates along Path III (ending in unilateral law) are very similar to those along Paths I and II. Roughly speaking, Path III is a vertical displacement of the first two. We do not offer an explanation of why Path III states (those that adopted unilateral law) have uniformly higher divorce rates than others throughout our sample period. We do find that the fall in the cost of divorce legislated by every state contributed to the rise in divorce rates and in similar ways along each of the three paths. All states achieved low divorce costs. Whether achieved by lowering wait times (Path I) or by adopting no fault grounds (Paths II and III) did not seem to matter. The short, medium and long run impacts of these cost reductions (i.e., the surprise, floodgate and selection effects) are similar for states on all three paths.

In general the CPDM highlights the profoundly contradictory nature of policy levers. In the CPDM, policies designed to reduce exit rates will never increase entry rates and may have the unintended consequence of reducing subsequent entry rates. Conversely, policies designed to promote entry will never reduce exits and may have the unintended consequence of increasing subsequent exit rates.

The cohort panel data model (CPDM) lives in the sparsely populated space between the estimation of fully articulated dynamic optimization models and the estimation of much simpler difference-in-difference models. As shown in the current application, the CPDM provides a rich framework with which to articulate and estimate the implications of dynamic models.

The economic model and empirical specification developed in this paper are applicable to a wide range of problems much more general than the particular application to divorce studied here. For example, due to lack of geocoding it is not uncommon for researchers to have little choice but to use panel data aggregated to some level such as the state in place of their first choice, panel data on individuals. It is generally true that circumstances at a point in time t (e.g., divorce laws) change in a discrete manner. Here we have shown how the dynamic properties of such decisions can be estimated econometrically by carefully tracking the appropriate cohorts.[42]

[42] The effect of the contemporaneous stringency of criminal law on recidivism rates for recently released prisoners is one example. Define two incarceration cohorts, those imprisoned when stringency was high and those when low. The marginal prisoner is more hardened when laws are less stringent and fewer criminals are locked up. Then the effect of current stringency on recidivism rates would be affected by the shares of these two incarceration cohorts in the population of released prisoners.

APPENDIX

A Model of floodgate effects

Heterogeneity in marriage quality: the good, the bad and the lovely. To motivate our non-parametric specification of floodgate effects, we sketch a simple two-quality model of unobserved within-cohort marriage quality and then analyze the response of the cohort divorce rate to a surprise adoption of unilateral law. We show that the expected rate of decrease of the stock of bad marriages exceeds that for the good marriages by a constant. A parallel result holds for these expected stocks holds in response to a surprise reduction in divorce costs.

For the m^{th} married cohort in (s,t), let G_{st}^m and B_{st}^m be the number of high quality and low quality marriages, respectively, (henceforth *good* and *bad).* For the i^{th} individual in cohort m in (s,t), we specify the linear divorce probability as

$$d_{ist} = \alpha + \underset{(-)}{\beta}{}' c_{is}^m + \underset{(-)}{\mu}{}' U_{is}^m + \big(\underset{(-)}{\beta + I_i^B\theta_\beta}\big)(c_{ist} - c_{is}^m) + \big(\underset{(+)}{\mu + I_i^B\theta_\mu}\big)(U_{ist} - U_{is}^m) + X_{ist}'\eta + \epsilon_{ist} \ , \quad (20)$$

where $I_i^B = 0$ if i is in a good marriage and $I_i^B = 1$ if i is in a bad marriage with $\theta_\beta < 0$ and $\theta_\mu > 0$. These signs guarantee that, in response to liberalizing surprises, bad marriages will have a bigger increase in their permanent divorce rate than good marriages. Within each quality, aggregate over individuals to get the divorce rates for the good $\left(d_{st}^{mG}\right)$ and the bad marriages $\left(d_{st}^{mB}\right)$, as

$$\begin{aligned} d_{st}^{mG} &= \tfrac{1}{N_{st}^{mG}} \sum_{i\in\left\{I_i^G=0\right\}} d_{ist} = d_{st}^{m*} + \beta\left(c_{st} - c_s^m\right) + \mu(U_{st} - U_s^m) + \epsilon_{st}^{mG} \ , \\ d_{st}^{mB} &= \tfrac{1}{N_{st}^{mB}} \sum_{i\in\left\{I_i^B=1\right\}} d_{ist} = d_{st}^{m*} + (\beta + \theta_\beta)\left(c_{st} - c_s^m\right) + (\mu + \theta_\mu)\left(U_{st} - U_s^m\right) + \epsilon_{st}^{mB} \ . \end{aligned} \quad (21)$$

Here, to highlight the surprise terms, all of the remaining systematic terms that are common to both the good and bad divorce equations are collected into d_{st}^{m*}.[43] Define the good and bad subcohort shares as

$$g_{st}^{mG} = \frac{G_{st}^m}{G_{st}^m + B_{st}^m} \text{ and } g_{st}^{mB} = \frac{B_{st}^m}{G_{st}^m + B_{st}^m}, \text{ where } g_{st}^{mG} + g_{st}^{mB} = g_{st}^{mB}. \quad (22)$$

Then write the m^{th} cohort's divorce rate as the weighted sum of the good and bad rates (21),

$$d_{st}^m = g_{st}^{mG} d_{st}^{mG} + g_{st}^{mB} d_{st}^{mG} = d_{st}^{m*} + \left(\beta + g_{st}^{mB}\theta_\beta\right)\left(c_{st} - c_s^m\right) + \left(\mu + g_{st}^{mB}\theta_\mu\right)\left(U_{st} - U_s^m\right) + \epsilon_{st}^m \ . \quad (23)$$

[43] Note that from this level of aggregation on up to the state level, the errors are heteroskedastic. But since the underlying individual errors, ϵ_{ist}, are assumed *i.i.d.*, we can and do account for heteroskedasticy at the state level without analyizing it at lower levels of aggregation.

Here $\epsilon_{st}^{m} = \left[\left(g_{st}^{mG}\epsilon_{st}^{mG} + g_{st}^{mB}\epsilon_{st}^{mB}\right)\right]$. Thus, at the cohort level, the absolute value of the coefficient on each surprise term grows in magnitude with the share of bad marriages in the cohort.[44] Consequently, how this share evolves over time determines the serial responses to surprises.

Intuitively, a surprise leads to an immediate spike in the divorce rate as both good and bad marriages now dissolve at higher rates. However, in that period and each following periods, the bad marriages divorce at a higher rate than the good ones, leaving relatively fewer bad marriages for the next period. Consequently with each passing period, the overall cohort divorce falls as it gets closer and closer to the rate of divorce for the good marriages. The result is a pattern we term a floodgate effect in which a liberalizing surprise leads to an immediate spike in the divorce rate, followed by a period-by-period declines, reflecting the successive weeding out of bad marriages relative to good. Asymptotically, only good marriages survive with divorce rates $d_{st}^{m*} + \beta\left(c_{st} - c_{s}^{m}\right) + \mu(U_{st} - U_{s}^{m}) + \epsilon_{st}^{m}$ which is expected to be higher than the pre-surprise rate by $\beta\left(c_{st} - c_{s}^{m}\right) + \mu(U_{st} - U_{s}^{m})$ and lower than the spike by $g_{st}^{mB}\theta_{\beta}\left(c_{st} - c_{s}^{m}\right) + g_{st}^{mB}\theta_{\mu}(U_{st} - U_{s}^{m})$. Clearly, the rate of decline of the divorce rate will be faster the smaller the share of bad marriages at the time of the surprise g_{st}^{mB} and the more exaggerated the response (relative to the good marriages) of the bad marriages to the surprise ($|\theta_{\beta}|$ and θ_{μ}).

First, we show that, following a liberalizing surprise in the right to divorce, the expected number of good marriages does not shrink as fast as the expected number of bad marriages as they differ by a constant. The analogous argument goes through for a surprise reduction in the cost of divorce. While formally, we would like to show that This is sufficient to motivate our non-parametric representation of floodgate effects for both surprise liberalizations of rights and surprise reductions in costs.

Consider a *ceteris paribus* permanent change in the right to divorce at $t = \tau$ with no change in the cost of divorce.[45] This means that before τ, there was no surprise$(U_{st} - U_{s}^{m}) = 0$, and that after that, for $t = \tau,\ \tau + 1,\ \tau + 2, \ldots$, we have$(U_{st} - U_{s}^{m}) = 1$. The restrictions $(c_{st} - c_{s}^{m}) = 0$ and $d_{s\tau}^{m*} = d_{s,\tau+1}^{m*} = d_{s,\tau+2}^{m*} = d_{s,\tau+3}^{m*} = \ldots$ embody the *ceteris paribus* condition. Thus, for $t = \tau,\ \tau + 1,\ \tau + 2, \ldots$ the good and bad divorce equations (21) become

$$\begin{aligned} &d_{st}^{mG} = d_{s\tau}^{m*} + \mu + \epsilon_{st}^{mG}\ , \\ &\text{and} \\ &d_{st}^{mB} = d_{s\tau}^{m*} + (\mu + \theta_{\mu}) + \epsilon_{st}^{mB}. \end{aligned} \tag{24}$$

Apart for random errors, each of these divorce rates remains constant after the surprise. In the overall cohort rate, however, the weight (share) of each of these rates (23) evolves systematically over time.

In cohort m the populations of both good and bad marriages decline according to the iterative

[44] At this point we could also introduce (i) within cohort heteroskedasticity and (ii) marriages that are bad in terms of cost surprises but not in terms of a suprise to rights. With regard to (i), we choose not to, because our model is already a considerable generalization of the models in the literature and we are pushing on the limit of the number of coefficients one can estimate from state panel data. We chose to spend our degrees of freedom on parameters with more interesting economic interpretations. Witih regard to (ii), we allow for this in the empirical section, but do not develop the full notation here.

[45] Since, analytically, a ceteris paribus change in the right to divorce is the easiest place to start, we do so. However, we emphasize that in the real world, whenever a state adoped unilateral law, it also simultaneously reduced the cost of divorce to w^{N} from some greater cost; see Section 2.5.

relationships,[46]

$$
\begin{array}{l}
G^m_{s,\tau+k} = G^m_{s,\tau+k-1}\left[1-\left(d^{m*}_{s,\tau}+\mu+\epsilon^{mG}_{s,\tau+k-1}\right)\right], \\
\text{and} \\
B^m_{s,\tau+k} = B^m_{s,\tau+k-1}\left[1-\left(d^{m*}_{s,\tau}+\mu+\theta_\mu+\epsilon^{mB}_{s,\tau+k-1}\right)\right], \text{ for } k=1,2,\ldots\ .
\end{array}
\tag{26}
$$

Let $r^{mG}_{s,\tau+k}$ and $r^{mB}_{s,\tau+k}$ stand for the growth rates for the numbers of good and bad marriages between $\tau+k-1$ and $\tau+k$. Then,

$$
\begin{array}{l}
1+r^{mG}_{s,\tau+k} = \frac{G^m_{s,\tau+k}}{G^m_{s,\tau+k-1}} = \left[1-\left(d^{m*}_{s,\tau}+\mu+\epsilon^{mG}_{s,\tau+k-1}\right)\right], \\
\text{and} \\
1+r^{mB}_{s,\tau+k} = \frac{B^m_{s,\tau+k}}{B^m_{s,\tau+k-1}} = \left[1-\left(d^{m*}_{s,\tau}+\mu+\theta_\mu+\epsilon^{mB}_{s,\tau+k-1}\right)\right]\ .
\end{array}
\tag{27}
$$

Solving (27) for the growth rates yields

$$
\begin{array}{l}
r^{mG}_{s,\tau+k} = -\left(d^{m*}_{s,\tau}+\mu+\epsilon^{mG}_{s,\tau+k-1}\right), \\
\text{and} \\
r^{mB}_{s,\tau+k} = -\left(d^{m*}_{s,\tau}+\mu+\theta_\mu+\epsilon^{mB}_{s,\tau+k-1}\right)
\end{array}
$$

for a difference in rates of

$$
r^{mB}_{s,\tau+k} - r^{mG}_{s,\tau+k} = -\theta_\mu + \left(\epsilon^{mG}_{s,\tau+k-1} - \epsilon^{mB}_{s,\tau+k-1}\right) \tag{28}
$$

and with the expectation of the difference being

$$
E\left[r^{mB}_{s,\tau+k} - r^{mG}_{s,\tau+k}\right] = -\theta_\mu < 0. \tag{29}
$$

That is, the expected the stock of bad marriages shrinks faster than that of good marriages by a constant margin, $-\theta_\mu$.

Thus, we expect the following pattern of divorce rates in response to a surprise liberalization of rights. In τ, the period of the shock, divorces from both good and bad marriage increase and cohort divorce rate spikes, increasing by $\left(\mu + g^{mB}_{st}\theta_\mu\right)$. Thereafter, period by period, due to divorces in the previous period, we expect the shrinkage in the stock of bad marriages to exceed the shrinkage of the stock of good marriages by $-\theta_\mu$, thereby lowering the overall cohort divorce rate. Ultimately, as bad marriages get relatively more and more scarce, the response of the cohort's divorce rate approaches μ, that of the good marriages.

What we would really like to show is that $\underset{k\to\infty}{lim} E\left[g^{mG}_{s,\tau+k}\right] = 0$. The difficulty is that random errors reside in both the numerator and denominator of $g.$. Instead, we have shown enough so that the weaker condition, $p\lim_{k\to\infty}\left[g^{mG}_{s,\tau+k}\right] = 0$ holds.

[46] Then, for a shock to divorce righes in $t=\tau$, i.e., for $U_{s\tau} - U^m_s = 1$, we have

$$
\begin{array}{l}
d^{mG}_{s\tau} = d^{m*}_{s\tau} + \mu + \epsilon^{mG}_{s\tau}\ , \\
\text{and} \\
d^{mB}_{s\tau} = d^{m*}_{s\tau} + (\mu+\theta_\mu) + \epsilon^{mB}_{s\tau}
\end{array}
\tag{25}
$$

From the good marriages, this yields $\left(d^{m*}_{s\tau}+\mu+\epsilon^{mG}_{s\tau}\right)G^m_{s\tau}$ divorces and $G^m_{s,\tau+1} = G^m_{s\tau}\left[1-\left(d^{m*}_{s\tau}+\mu+\epsilon^{mG}_{s\tau}\right)\right]$ good mariages that survive until $\tau+1$. From these, we will get $\left(d^{m*}_{s,\tau+1}+\mu+\epsilon^{mG}_{s,\tau+1}\right)G^m_{s,\tau+1}$ divorces in $\tau+2$, and $G^m_{s,\tau+2} = G^m_{s,\tau+1}\left[1-\left(d^{m*}_{s,\tau+1}+\mu+\epsilon^{mG}_{s,\tau+1}\right)\right]$ good mariages that survive until $\tau+3$, and so on.

B Estimated floodgate effects

The columns in Table 6 and (7)give the estimated floodgate effects for the corresponding columns in Tables 4 and 5, respectively.

	CPDM Extra Floodgate Effects $\delta^{\mu}, \delta^{\beta}, \delta^{\beta w^N}$ free		**CPDM** Exact Floodgate Effects $\delta^{\mu}, \delta^{\beta}$ free $\delta^{\beta w^N} = \delta^{\beta}$	
	(1)	(2)	(3)	(4)
δ^{μ}_{4-6}	1.930 [0.495]†		1.591 [0.571]	
δ^{μ}_{7-9}	3.855 [0.341]		3.422 [0.324]	
δ^{μ}_{10-12}	6.835 [0.293]		5.902 [0.274]	
δ^{μ}_{13+}	4.663 [0.679]		5.392 [0.365]	
δ^{β}_{4-6}	1.073 [0.747]	1.073 [0.746]	1.183 [0.112]	1.005 [0.965]
δ^{β}_{7-9}	1.377 [0.253]	1.384 [0.243]	1.469** [0.012]	0.687 [0.114]
δ^{β}_{10-12}	1.607 [0.187]	1.627 [0.172]	1.917*** [0.001]	0.206** [0.014]
δ^{β}_{13+}	1.503 [0.422]	1.542 [0.384]	1.793* [0.088]	0.291* [0.062]
$\delta^{\mu} = \iota$	[0.885]‡	✓	[0.869]	✓
$\delta^{\beta} = \iota$	[0.658]	[0.636]	[0.024]	[0.094]
$\delta^{\beta w^N} = \delta^{\beta}$	[0.964]	[0.302]	✓	✓

N=1343. Estimates from population-weighted GLS regressions with first order autocorrelated errors within states, state and year FE's, and linear and quadratic state-specific time trends.
† $p-$values for the test that the coefficient equals 1 in brackets.
(*,**,***) indicate 'significance' at the (.10, .05, and .01) levels, respt.
‡ $p-$values. ✓ indicates the hypothesis is maintained. Tx.

Table 6: Floodgate effects for estimates of CPDM in Table 4

(12) Wolfers + costs			(13) Wolfers	
δ^{μ}_{4-6}	2.080 [0.412]		δ^{μ}_{3-4}	1.029 [0.943]
δ^{μ}_{7-9}	3.948 [0.295]		δ^{μ}_{5-6}	0.819 [0.753]
δ^{μ}_{10-12}	6.216 [0.264]		δ^{μ}_{7-8}	0.076 [0.219]
δ^{μ}_{13+}	4.875 [0.594]		δ^{μ}_{9-10}	-1.062^{*} [0.077]
			δ^{μ}_{11-12}	-2.009^{*} [0.057]
			δ^{μ}_{13-14}	-1.713^{*} [0.097]
			δ^{μ}_{15+}	-0.207 [0.411]
δ^{β}_{4-6}	0.935 [0.448]			
δ^{β}_{7-9}	0.941 [0.567]			
δ^{β}_{10-12}	0.994 [0.964]			
δ^{β}_{13+}	0.945 [0.591]			
Test of:				
$\delta^{\mu} = \iota$	[0.863]‡			[0.615]
$\delta^{\beta} = \iota$	[0.914]			✓

N=1343. Estimates from population-weighted GLS regressions with first order autocorrelated errors within states, state and year FE's, and linear and quadratic state-specific time trends.
† $p-$value for the test that the coefficient is equal to 1 in parentheses.
*,**,*** indicate 'significance' at the (.10, .05, and .01) levels, respt.
‡ $p-$values. ✓ indicates the hypothesis is maintained.

Table 7: Floodgate effects for specifications (12) and (13) in Table 5

C Four terms in the CPDM; two terms in the static model

Term by term substitution into (7) takes advantage of the convention that the last cohort is numbered the 5^{th} and only the 5^{th} cohort can marry under any of the three regimes, i.e., under R_{st}^{II} or under R_{st}^{III} as well as under R_{st}^{I}. Define $\omega_s^m = \omega\left(w_s^m, w^*\right)$. Then for $m = 1, 2, 3, 4$ we have $c_s^m = \omega_s^m = \omega\left(w_s^m, w^*\right) = w_s^m + \left(w^* - w_s^m\right) I\left(w_s^m > w^*\right)$. Thus the variable for the selection on cost of divorce at the time of marriage in (8) is

$$\begin{aligned}
&\sum_{m=1}^{5} g_{st}^m c_s^m = \sum_{m=1}^{4} g_{st}^m c_s^m + g_{st}^5 c_s^5 \\
&= \sum_{m=1}^{4} g_{st}^m \omega\left(w_s^m, w^*\right) + g_{st}^5 \omega\left(w_s^5, w^*\right) R_{st}^I + w^N g_{st}^5\left(R_{st}^{II} + R_{st}^{III}\right) \\
&= \begin{cases}
\sum_{m=1}^{4} g_{st}^m \omega\left(w_s^m, w^*\right), \quad t \text{ such that } g_{st}^5 = 0 \\
\sum_{m=1}^{4} g_{st}^m \omega\left(w_s^m, w^*\right) + g_{st}^5 \omega\left(w_s^5, w^*\right) R_{st}^I + w^N g_{st}^5\left(R_{st}^{II} + R_{st}^{III}\right), t \text{ such that } 0 < g_{st}^5 < 1 \\
\omega\left(w_{st}, w^*\right) R_{st}^I + w^N\left(R_{st}^{II} + R_{st}^{III}\right), \quad t \text{ such that } g_{st}^5 = 1 \ .
\end{cases}
\end{aligned} \tag{30}$$

The term is thus β' times this expression.

The cost surprises terms at (s,t) is $\beta L\left(l_{st}, \delta^\beta\right)\left(c_{st} - \sum_{m=1}^{5} g_{st}^m c_s^m\right)$. The expression in parentheses can be written as

$$\begin{aligned}
&c_{st} - \sum_{m=1}^{5} g_{st}^m c_s^m = c_{st} - \sum_{m=1}^{4} g_{st}^m c_s^m - g_{st}^5 c_s^5 \\
&= \begin{cases}
c_{st} - \sum_{m=1}^{4} g_{st}^m \omega\left(w_s^m, w^*\right) \ , \quad t \text{ such that } g_{st}^5 = 0 \\
c_{st} - \sum_{m=1}^{4} g_{st}^m \omega\left(w_s^m, w^*\right) - g_{st}^5 \omega\left(w_s^5, w^*\right) R_{st}^I - w^N g_{st}^5\left(R_{st}^{II} + R_{st}^{III}\right), t \text{ such that } 0 < g_{st}^5 < 1 \\
c_{st} - c_{st} = 0 \ , \quad t \text{ such that } g_{st}^5 = 1
\end{cases}
\end{aligned} \tag{31}$$

Note that the very last line of (31) says that in the long run (as g_{st}^5 approaches 1) and everyone is in the 5^{th} (i.e., the most recent or last) marriage cohort, there are no surprises.

Recall that the homogeneous cohort CPDM is the special case of the CPDM with no floodgate effects $\left(L\left(l_{st}, \delta^\beta\right) = L\left(l_{st}, \iota\right) = 1\right)$. Then from (30) and (31) it is easy to see that if we further impose the restriction $\beta' = \beta$, namely that cohorts not yet married respond in the same way to a change in the cost of divorce as already married cohorts, then

$$\beta' \sum_{m=1}^{5} g_{st}^m c_s^m + \beta\left(c_{st} - \sum_{m=1}^{5} g_{st}^m c_s^m\right) = \beta c_{st} \ . \tag{32}$$

Thus the static model wipes out essential features of the underlying dynamic optimization model, namely that a drop in the cost of divorce before marriage has a selection effect (β'), and a drop in the cost of divorce after marriage has a surprise effect (β), and that these two effects are essentially different.

Turning to the terms capturing the effects of changing the right to divorce, note that

$$\sum_{m=1}^{5} g_{st}^{m} U_{s}^{m} = \sum_{m=1}^{4} g_{st}^{m} \cdot 0 + g_{st}^{5} U_{s}^{5} = g_{st}^{5} U_{st} \ . \tag{33}$$

Thus, the selection term on the unilateral right to divorce reduces to $\mu' g_{st}^{5} U_{st}$. Similarly, for the measure of surprise,

$$(U_{st} - \sum_{m=1}^{5} g_{st}^{m} U_{s}^{m}) = (U_{st} - g_{st}^{5} U_{st}) = (1 - g_{st}^{5}) U_{st} \ . \tag{34}$$

Thus the unexpected right to unilateral divorce yields the surprise term $\mu L(l_{st}, \delta^{\mu})(1 - g_{st}^{5}) U_{st}$ and therefore the entire effect of the adoption of the unilateral right to divorce is

$$\mu' g_{st}^{5} U_{st} + \mu L(l_{st}, \delta^{\mu})(1 - g_{st}^{5}) U_{st} \ . \tag{35}$$

Recall that the homogeneous cohort CPDM is the special case of the CPDM with no floodgate effects ($L\left(l_{st}, \delta^{\mu}\right) = L\left(l_{st}, \iota\right) = 1$). Then from (33) and (34) it is easy to see that if we further impose the restriction $\mu' = \mu$, namely that cohorts not yet married respond in the same way to the adoption of the unilateral right to divorce as already married cohorts, then

$$\mu' g_{st}^{5} U_{st} + \mu U_{st} \left(1 - g_{st}^{5}\right) = \mu U_{st} \ . \tag{36}$$

In parallel to the result for the cost terms, this wipes out the remaining essential features of the underlying dynamic optimization model, namely that the adoption of unilateral law before marriage has a selection effect (μ'), the adoption of unilateral law after marriage has a surprise effect (μ), and that these two effects are essentially different.

Collecting these four terms and Making three Taylor expansions results in

$$\begin{aligned}
&d_{st} = \alpha \\
&+\beta' \cdot \sum_{m=1}^{5} g_{st}^{m} [\Big[w_{s}^{m} + (w_{(r)}^{*} - w_{s}^{m}) I\left(w_{s}^{m} > w_{(r)}^{*}\right)] + \gamma_{m}' I(w_{s}^{m} > w_{(r)}^{*})\Big]] R_{st}^{I} + \beta' w^{N} \cdot g_{st}^{5}\left(R_{st}^{II} + R_{st}^{III}\right) \\
&+\beta \cdot \Bigg(\Big\{\Big[[w_{st} + (w_{(r)}^{*} - w_{st}) I\left(w_{st} > w_{(r)}^{*}\right)] + \gamma I\left(w_{st} > w_{(r)}^{*}\right)\Big] R_{st}^{I}\Big\} \\
&\qquad - \sum_{m=1}^{5} g_{st}^{m} [\Big[w_{s}^{m} + (w_{(r)}^{*} - w_{s}^{m}) I\left(w_{s}^{m} > w_{(r)}^{*}\right)] + \gamma_{m} I(w_{s}^{m} > w_{(r)}^{*})\Big]] R_{st}^{I}\Bigg) \\
&+\beta w^{N} \cdot \left(1 - g_{st}^{5}\right)\left(R_{st}^{II} + R_{st}^{III}\right) + \mu' \cdot g_{st}^{5} U_{st} + \mu \cdot U_{st}\left(1 - g_{st}^{5}\right) + \epsilon_{st}, \quad ,
\end{aligned} \tag{37}$$

Presumed correction

$$d_{st} = \alpha + \beta' \cdot \sum_{m=1}^{5} g_{st}^{m} [w_s^m + (w^*_{(r)} - w_s^m) I \left(w_s^m > w^*_{(r)} \right)] R_{st}^I + \gamma' \cdot \sum_{m=1}^{5} g_{st}^m \, I(w_s^m > w^*_{(r)}) R_{st}^I$$
$$\beta \cdot \left\{ [w_{st} + (w^*_{(r)} - w_{st}) I \left(w_{st} > w^*_{(r)} \right)] - \sum_{m=1}^{5} g_{st}^m [w_s^m + (w^*_{(r)} - w_s^m) I \left(w_s^m > w^*_{(r)} \right)] \right\} R_{st}^I +$$
$$\gamma \left\{ \cdot I \left(w_{st} > w^*_{(r)} \right) - \sum_{m=1}^{5} g_{st}^m \, I(w_s^m > w^*_{(r)}) \right\} R_{st}^I$$
$$+\beta' w^N \cdot g_{st}^5 \left(R_{st}^{II} + R_{st}^{III} \right) + \beta w^N \cdot \left(1 - g_{st}^5 \right) \left(R_{st}^{II} + R_{st}^{III} \right) + \mu' \cdot g_{st}^5 U_{st} + \mu \cdot U_{st} \left(1 - g_{st}^5 \right) + \epsilon_{st}. \quad (38)$$

D States on each path to easy divorce

Paths started in R^I and as of 1988 were in	**States**	**Number**
Regime I: $w \leq w^*$	AR, DC, IL, LA, MD, NJ, NY, NC, OH, SC, VT, VA	12
Regime II: bilateral-no-fault	DE, MS, PA, SD, TN, WI	6
Regime III: unilateral-no-fault	AL, AZ, CA, CO, CT, FL, GA, HI, ID, IN, IA, KS, KY, ME, MA, MI, MN, MO, MT, NE, NV, NH, ND, OR, RI, TX, UT, WA, WV, WY	30
In Regime III before 1962	AK, NM, OK adopted unilateral laws in 1935, 1933 and 1953, respectively.	3
N O T E S	These paths pertain to our sample period, 1956-1988. Subsequently, Ohio and NJ added no-fault grounds (R^{II}) in 1990 and 2007, respectively. In 2010, New York implemented unilateral divorce (R^{III}).	

Table 8: The States' Paths to Easy Divorce, 1956-1988

References

Becker, G. (1981). *A Treatise on the Family*. Cambridge, Mass.: Harvard University Press.

Bertrand, M., E. Duflo, and S. Mullainathan (2004). How much should we trust differences in differences estimates? *The Quartely Journal of Economics 119*(1), 249–275.

Brown, M. and C. J. Flinn (2006). Investment in child quality over marital states. University of Wisconsin and New York University working paper.

Caceres-Delpiano, J. and E. Giolito (2008a). How unilateral divorce affects children. IZA Disussion Paper No. 3342.

Caceres-Delpiano, J. and E. Giolito (2008b, April). The impact of unilateral divorce on crime. Universidad Carlos III de Madrid working paper.

Chiappori, P.-A., B. Fortin, and G. Lacroix (2002). Marriage market, divorce legislation, and houshold labor supply. *Journal of Political Economy 110*, 37–72.

Clark, S. (1999, March). Law, property, and marital dissolution. *Economic Journal 109*(454), C41–54.

Dickert-Conlin, S. and S. Houser (2002, March). EITC and marriage. *National Tax Journal 55*(1), 25–40.

Fonzo, J. H. D. (1997). *Beneath the Fault Line*. Charlottesville: University of Virginia Press.

Friedberg, L. (1998). Did unilateral divorce raise divorce rates? evidence from panel data. *American Economic Review 88*(3), 608–627.

Friedman, L. (2000). A dead language: Divorce law and practice before no-fault. *Virginia Law Review 86*(7), 1497–1536.

Friedman, L. M. (1984). Rights of passage: Divorce law in historical perspective. *Oregon Law Review 63*, 649–670.

Friedman, L. M. (2004). *Private Lives: Families, Individuals, and the Law*. Cambridge: Harvard University Press.

Gold, M. C. (2008). Divorce and divorce reforms: A reconciliation of results at odds. University of Wisconsin at Madison working paper.

Gray, J. S. (1998, June). Divorce law changes, household bargaining, and married women's labor supply. *American Economic Review 88*(3), 628–642.

Gruber, J. (2004). Is making divorce easier bad for children? the long-run implications of unilateral divorce. *Journal of Labor Economics 22*(4), 799–834.

Muggeo, V. (2003). Estimating regression models with unknown break-points. *Statistics in Medicine 22*(19), 3055–3071.

Peters, H. (1986). Marriage and divorce: Informational constraints and private contracting. *American Economic Review 76*(3), 437–454.

Rasul, I. (2006). Marriage markets and divorce laws. *Journal of Law, Economics, and Organization 22*(1), 30–69.

Rasul, I. (2008). The economics of the marriage contract: Theories and evidence. *Journal of Law and Economics 51*, 59–110.

Rheinstein, M. (1972). *Marriage Stability, Divorce, and the Law*. Chicago: University of Chicago Press.

Sugarman, S. D. and H. H. Kay (1990). *Divorce Reform at the Crossroads*. New Haven: Yale University Press.

Sun, H. (2008, October). Child support policy and divorce. Working Paper.

Tartari, M. (2007, May). Divorce and the cognitive achievement of children. Yale University working paper.

Weiss, Y. and R. J. Willis (1997, January). Match quality, new information, and marital dissolution. *Journal of Labor Economics 15*(1), S293–S329.

Wolfers, J. (2006). Did unilateral divorce raise divorce rates? a reconciliation and new results. *American Economic Review 96*(5), 1802–1820.