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Abstract

This paper studies the hypothesis that marriage opportunities are an economic determinant of female prostitution. I exploit differences in the timing of entry into force of unilateral divorce laws across U.S. states to explore the effect of such laws on female prostitution (proxied by arrests of female prostitutes). Using a difference-in-difference estimation approach, I find that unilateral divorce reduces prostitution by 10%. My results suggest that unilateral divorce improves the option value of marriage by increasing wives' welfare. As a result, the opportunity cost of becoming a female prostitute increases and the supply of prostitution declines.

Keywords: Prostitution, unilateral divorce, difference-in-difference, marriage compensation

JEL codes: J12, J16, K14, K15, K36

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1 Introduction

Prostitution is a gender issue. According to HG.org (2017), of the total arrests for prostitution in the U.S., 70% are female prostitutes, 20% are either male prostitutes or pimps and the remaining 10% are prostitutes' clients.

Since the 1960s, combating prostitution has been a key target of many American policy interventions (Shively et al. 2012).[1] Recently, there have been important policy debates on prostitution (Della Giusta 2016; Yttergren and Westerstrand 2016). In particular, in 2014, the European Parliament voted in favor of a resolution to criminalize the purchase of prostitution. According to this school of thought, whether it is forced or voluntary, prostitution is a violation of human rights and human dignity. Prostitution laws aside, little is known about how to reduce prostitution.

In this paper, I study how a seemingly unrelated policy (namely, unilateral divorce) reduces prostitution. This result is aligned with a branch of the literature led by Edlund and Korn (2002). Edlund and Korn (2002) suggest two mechanisms that might explain such a reduction. I test several potential mechanisms, but I find empirical evidence in favor of only one of the two mechanisms hypothesized by Edlund and Korn (2002). Specifically, my results indicate that the enforcement of unilateral divorce laws ameliorates wives' welfare, thereby improving one of the main economic determinants of prostitution: prostitutes' outside options. Consequently, once prostitution is relatively less attractive, prostitution decreases.

Although the link between divorce regimes and prostitution may appear weak at first glance, there are several channels through which such a relationship could be established. For example, because the availability of unilateral divorce alters the bargaining position of partners within married couples relative to more rigid divorce regimes where mutual consent is required, introducing such a divorce law could impinge on prostitution via downward shifts in its demand and supply. On the one hand, it could be argued that those married men who are prostitutes' clients become more reluctant to purchase their services because their wives could dissolve their marriages more easily under unilateral divorce. As a result, this change in clients' behavior would translate into a reduction in the demand for prostitution. On the other hand, the threat of unilateral divorce may

[1] The first "reverse sting" operation to catch prostitutes' clients took place in Nashville, Tennessee, in 1964. Ten years later, considerable financial resources were devoted to arresting male customers in St. Petersburg, Florida, based on some of the main principles that were later used in the so-called "Nordic Model" (i.e., criminalizing the purchase of prostitution). In the same year, the first shaming campaign was started in Eugene, Oregon, in which names and/or photos of prostitutes' clients were publicized. Similarly, in 1995, the first school to re-educate arrested sex buyers opened in San Francisco. The vast majority of these policies were intended to combat prostitution by reducing its demand.

improve the conditions of married women and therefore make marriage a more attractive option, leading to a fall in the supply of prostitution. In either of these two cases, the entry into force of unilateral divorce laws reduces the amount of prostitution in equilibrium.

By the same token, there are reasonable alternative mechanisms that instead imply an increase in the amount of prostitution. For instance, it could be argued that unilateral divorce laws are likely to increase the number of divorces in the short term and therefore lead to a rise in the share of single people in the population. To the extent that single men demand more prostitution services than married men and insofar as single women supply more prostitution services than married women, these two forces could jointly lead to a larger amount of prostitution in equilibrium.

In view of the previous mechanisms, it seems relevant to determine the sign and size of the causal effect of unilateral divorce on prostitution as well as to identify its underlying mechanism. Indeed, the nature of this effect could change people's prior beliefs on these two issues. A negative effect could generate a trade-off for those who oppose divorce and prostitution: barriers to divorce would imply higher levels of prostitution. Conversely, a positive effect would reinforce their beliefs.

This paper addresses this issue by exploiting a quasinatural experiment provided by differences in the timing of the implementation of unilateral divorce laws across U.S. states. Such differences enable one to use a difference-in-difference approach (DiD hereafter) to identify the potential causal effect of such laws on the arrests of female prostitutes. Note that arrests for female prostitution are used as a proxy for the amount of prostitution, an activity for which there is very scant information given its illegality.[2] To implement the DiD approach, two sources of data are combined: the month in which unilateral divorce laws became effective in each U.S. state and information on arrests drawn from the agency-level UCR (Uniform Crime Reporting) database. The evidence provided in this paper relies on the plausible identification assumption that the month in which unilateral divorce laws became effective in each state was correlated neither with any crime pattern in general nor with any prostitution pattern in particular.

To assess the credibility of the previous identification assumption, I use an event study methodology in a time window close to the date of the policy intervention. The evidence obtained in this respect credibly shows that the effect on prostitutes' arrests occurs after the entry into force of the law and that prior to the intervention date, treated and control groups share a common underlying trend.

[2]The two variables are bound to move together if the arrest intensity for prostitutes is fairly constant over time, an assumption that I cannot directly test but that I regard as plausible. Moreover, insofar as my identifying variation – changes in unilateral divorce laws – does not covary with changes in the arrest intensity for prostitutes, my results are unaffected by changes to this intensity.

My main finding is that unilateral divorce laws reduce arrests for female prostitution by roughly 10%. Such a reduction takes place in the first year after the implementation of the law. Since approximately 60,000 female prostitutes are arrested on average in the U.S. each year, the abovementioned estimate implies a reduction of approximately 6,000 women arrested for prostitution. Using statistics from one of the main American law and government information sites, I find that this decrease yields a reduction in costs of approximately $16.4 million for American taxpayers.[3] It is possible to make a guess regarding the decrease in the overall number of female prostitutes by using information drawn from Fondation-Scelles (2012), which reports that there were approximately 1 million prostitutes in the U.S. during the 2000s. Using such a figure and my estimated effect, a simple back-of-the-envelope calculation indicates that unilateral divorce laws reduce the number of prostitutes by 100,000.

However, since in various states no-fault divorce laws went into effect slightly before unilateral divorce laws were enacted, one could be concerned that the former divorce laws also played an important role in the decline in arrests of female prostitutes to the extent that these laws reduced the cost of divorce relative to no-divorce (i.e., traditional) regimes. Using the month in which no-fault divorce laws entered into force as a further control in the DiD specification, I find that this factor does not change the previous estimate of the causal effect. An interpretation of this result is that no-fault divorce laws do not change the bargaining structure within couples but merely reduce the costs of filing for a divorce.

Next, I consider the potential mechanisms that could be driving the results. These mechanisms range from a general decline in the number of arrests for all types of crimes to changes in both the demand and supply of prostitution. First, I examine the mechanisms suggested by Edlund and Korn (2002). These are supply-driven mechanisms stemming from changes in the value of marriage as an outside option to prostitution. Namely, these two mechanisms are an increase in wives' wages and an improvement of conditions in marriage for wives (i.e., wives' welfare) that results from wives' greater bargaining power when unilateral divorce laws enter into force. Using data on the real average wage of wives across U.S. states, I do not find empirical evidence to support the notion that unilateral divorce laws affect wives' real wages. Then, I analyze whether there is evidence of unilateral divorce law improving wives' conditions in marriage. If this were the case, it seems plausible to conjecture that only female prostitutes of marriageable and fertile age would exit prostitution since they would be the main beneficiaries of an improvement in wives' welfare (Edlund and Korn 2002; Edlund 2013). To test this hypothesis, I divide the

[3] Statistics are drawn from HG.org (2017).

data on arrests of female prostitutes into different age groups and find that female prostitutes of marriageable and fertile age are the main drivers of the estimated reduction in arrests of female prostitutes.

Second, I explore whether unilateral divorce laws led to a general reduction in arrests for crimes not connected to prostitution per se. Using data on police officers and on women arrested for robberies, drug crimes/usage and vandalism' (three crimes with higher frequency than prostitution), I find that these alternative crimes are not affected by the implementation of unilateral divorce laws.

Finally, I examine whether unilateral divorce changed the demand for prostitution. Three separate data sets are used to capture different features of such demand. In particular, data on the number of internet searches for several words connected to prostitution are used to proxy for online demand for prostitution; panel-survey data are used to analyze whether men's views toward prostitution change after men are divorced, and data on the number of unmarried men are used to proxy for the demand for prostitution by unmarried men. I do not find empirical support in any of these exercises that unilateral divorce decreases the demand for prostitution.

This paper contributes to three different lines of research. First, the empirical findings of this paper complement scholarship on the determinants of prostitution and on the relevance of several mechanisms at play in economic models of prostitution. There is a growing literature in economics and other social sciences that has studied prostitution from both theoretical and empirical perspectives (see, inter alia, Cameron 2002; Edlund and Korn 2002; Cameron and Collins 2003; Moffatt and Peters 2004; Gertler et al. 2005; Levitt and Venkatesh 2007; Arunachalam and Shah 2008; Della Giusta et al. 2009; Edlund et al. 2009; Della Giusta 2010; de la Torre et al. 2010; Cunningham and Kendall 2010, 2011c,a; Gertler and Shah 2011; Islam and Smyth 2012; Cunningham and Kendall 2013; Arunachalam and Shah 2013; Logan and Shah 2013; Shah 2013; Immordino and Russo 2014; Bisschop et al. 2015; Immordino and Russo 2015a,b; Cunningham and Shah 2016; Sohn 2016; Cunningham and Shah 2017; Ciacci and Sviatschi 2016).

In particular, the literature has analyzed what is known as the *prostitution wage premium puzzle*: prostitution is low skilled, labor intensive, and female dominated but well paid. Scholars have explained this puzzle with supply-side hypotheses. On the one hand, Gertler et al. (2005) argue that prostitutes earn a wage premium by providing unprotected sex. According to this hypothesis, prostitutes are willing to face the risk of contracting sexually transmitted infections since customers are willing to pay more to avoid using condoms. On the other hand, Della Giusta et al. (2009) claim that this wage premium can be explained by the low reputation that prostitution has and the social stigma it faces.

Finally, Edlund and Korn (2002) suggest that marriage compensation is key to understanding the *prostitution wage premium puzzle*: marriage market prospects are an important source of income for women, but by entering into prostitution, women compromise such prospects. The present paper tests this third hypothesis and finds evidence in its favor.[4] In addition, a strand of the literature has focused on analyzing how policy interventions connected to prostitution regulation affect other crimes. For example, Jakobsson and Kotsadam (2013); Cho et al. (2013); Lee and Persson (2015) study the link between human trafficking and prostitution, while Ciacci and Sviatschi (2016); Cunningham and Shah (2017); Bisschop et al. (2015) analyze how changes in prostitution policies or business establishments connected to prostitution affect sex crimes. However, to the best of my knowledge, this is the first paper that examines how a policy intervention outside the prostitution market affects the latter.

Second, this paper contributes to a stream of research in sociology, law and economics that evaluates the impact of unilateral divorce laws on various outcomes (see, e.g., Weitzman (1985); Gray (1998); Friedberg (1998); Edlund and Pande (2002); Gruber (2004); Rasul (2004, 2005); Alesina and Giuliano (2007); Stevenson and Wolfers (2006, 2007); Stevenson (2008); Wickelgren (2007); Voena (2015)). However, none on these papers addresses the effects of these laws on prostitution.

Finally, the results of this paper also contribute to a growing line of the literature in sociology, criminology and economics that studies the effect of changing the opportunity cost of criminals on crime (see, e.g., Raphael and Weiman (2007); Raphael (2010); Beauchamp and Chan (2014); Uggen and Shannon (2014); Cook et al. (2015); Doleac and Hansen (2016); Doleac (2016); Agan and Starr (2017); Schnepel (2017); Yang (2017); Agan and Makowsky (2018); Tuttle (2019)).

The remainder of the paper is organized as follows. Section 2 proposes a conceptual framework explaining the main hypothesis tested throughout this paper. Section 3 describes the data sets used in this paper. Section 4 discusses the estimation approach and the main results obtained. Section 5 examines the identification assumption of the regression models. Section 6 tests the robustness of the results. In section 7, I empirically explore the numerous underlying mechanisms that might explain the findings of the paper. Finally, Section 8 concludes the paper.

[4]Specifically, the present paper also contributes to a specific line of research (Arunachalam and Shah 2008; Cunningham and Kendall 2011b; Immordino and Russo 2015a) that tests the aforementioned mechanisms.

2 Conceptual framework: The link between unilateral divorce and prostitution

This paper tests a specific mechanism that is a byproduct of two branches of the literature. The first studies the effect of unilateral divorce on several outcomes related to wives' welfare. This line of research finds that unilateral divorce has a positive effect on wives' welfare. The second branch analyzes the determinants of prostitution; namely, this line of research explains the *prostitution wage premium puzzle*: prostitution is low skill, labor intensive, female dominated, and well paid.[5]

The Coase theorem predicts that if there are zero transaction costs and transferable utility, moving from mutual to unilateral divorce should not have any effect on divorce rates. Unilateral divorce simply reassigns property rights but does not change the outcome. Regardless of the divorce regime, only relationships with joint utility that is greater under marriage than under divorce survive. Therefore, the divorce rate would not change. However, both assumptions of the Coase theorem seem unrealistic in a marriage relationship. First, it is likely that bargaining is costly between spouses due to feelings and disdain. Second, utility might not be transferable between spouses.

Despite the predictions of the Coase theorem, moving from mutual to unilateral divorce entails huge redistributional differences between spouses. Under mutual consent divorce, the spouse who wishes to dissolve the marriage should compensate the other for the divorce. Conversely, unilateral divorce grants the property right to dissolve the marriage to the spouse who is better off with a divorce. Then, the spouse who wishes to remain married is the one who should compensate the partner to avoid divorce. Such distributional changes imply that the party seeking a divorce would be the one benefiting from the enforcement of a unilateral divorce law.

According to the literature, this party seems to be the wife. Indeed, the literature has found that unilateral divorce laws increase wives' welfare. Specifically, Stevenson and Wolfers (2006) find that unilateral divorce laws decrease female suicides, the number of women murdered by their partners and domestic violence, while Alesina and Giuliano (2007) report evidence on how these laws decrease out-of-wedlock births and increase fertility rates in the first years of marriage. They also document that unilateral divorce laws reduce the number of never-married women. In line with these results, Stevenson (2008) finds that unilateral divorce laws increase the labor participation of both married and single women.

Regarding the prostitution market, scholars have explained the *prostitution wage pre-*

[5] Appendix Section A offers a brief overview of the prostitution market in the U.S.

mium puzzle with three supply-side hypotheses. First, Gertler et al. (2005) argue that prostitutes earn a wage premium by providing unprotected sex. This hypothesis states that prostitutes are willing to face the risk of contracting sexually transmitted infections since customers are eager to pay more to avoid using condoms. Second, Della Giusta et al. (2009) claim that the premium obtained by prostitutes can be explained by the low reputation that prostitution has and the social stigma it incurs. Finally, Edlund and Korn (2002) contend that choosing to be a prostitute jeopardizes one's marriage market prospects. Moreover, according to their paper, being a wife and a prostitute is largely incompatible.[6] As a result, female prostitutes earn high wages since they are being compensated for forgone marriage opportunities, despite prostitution being low skill and labor intensive. Another key feature of this model is that wives sell to husbands a share of their custodial rights (i.e., reproductive sex) in exchange for marriage compensation (i.e., a level of welfare) (Edlund 2013). Indeed, the custodial rights of children born out of wedlock formerly belonged solely to the mother, while the custodial rights of children born in a marriage belong to both parents. This result, combined with the fact that marriage has traditionally been an important source of pecuniary and non-pecuniary resources for women, implies that prostitution must pay better than other jobs to compensate for the opportunity cost of forgone marriage market earnings.

Relying on the previous ideas, this paper suggests a mechanism that connects these two lines of research; in doing so, this mechanism offers an empirical test of Edlund and Korn (2002). The introduction of unilateral divorce increases the bargaining power of the spouse seeking the divorce.[7] Hence, in a unilateral divorce regime, wives know that they will be able to be divorced irrespective of their earnings.[8] This feature makes marriage more attractive to women by facilitating the breakup of "wrong" marriages. Overall, in line with the previous literature quoted above, the availability of unilateral divorce boosts wives' welfare. Therefore, the main beneficiaries of the introduction of unilateral divorce are women who prefer to marry but would have opted to become prostitutes in the absence of such a law. In so doing, these women are able to exchange a share of their custodial rights for the marriage compensation. The main recipients of an increase in wives' welfare in marriage would be women who are able to marry and can exchange

[6]This claim, as the authors write, "rests on the assumption that men prefer their wives to be faithful (for instance, from a desire to raise biological children)".

[7]For further information on the introduction of unilateral divorce across U.S. states, Appendix Section B discusses the legislative context that led to the enactment of such laws.

[8]Assuming that a husband's earnings are higher than his wife's, under a mutual consent divorce regime, if a husband wished to divorce, he could "bribe" his wife. However, a wife could not afford to do so. Under unilateral divorce, a husband could still compensate his wife financially to avoid divorce. However, the wife would need to consent.

their "share" of custodial rights.[9]

3 Data description

This section provides information about the data sets used throughout the paper. My econometric analysis is based on two main data sets: the Uniform Crime Reporting program, which contains information on the number of arrested prostitutes for each agency level in the U.S., and the effective date of unilateral divorce laws across U.S. states. The observations are matched at the county and month levels. Moreover, I use multiple data sets to carefully explore each of the potential mechanisms behind my findings.

3.1 Arrests for prostitution

Since historical data on the number of female prostitutes are not available, I use the number of female prostitutes' arrests from agency-level UCR (Uniform Crime Reporting) sources as a proxy for this missing variable. This database contains information about monthly reports of arrests by age, sex, and race provided each year by law enforcement agencies in the U.S. There are 29 main categories of offenses in this database. Such categories cover several types of offenses, ranging from vandalism to gambling and from prostitution to larceny. In addition, they are divided into subcategories for a total of 43 different offenses.[10] Each year, law enforcement agencies communicate their reports to the Federal Bureau of Investigation (FBI), which compiles its database in the form of periodic nationwide assessments of reported crimes not available elsewhere in the criminal justice system.

These data were downloaded from the Inter-university Consortium for Political and Social Research (ICPSR) webpage. ICPSR stores such information each year, dividing it into five different components: (i) summary data, (ii) county-level data, (iii) incident-level data, the National Incident-Based Reporting System (NIBRS), (iv) hate crime data, and (v) various, mostly nonrecurring, data collections. ICPSR recorded such data from 1980 to 2014 with the exception of 1984, for which data are missing.

With these available data sources, I construct a panel that includes monthly information at the county level on the ratio between the number of female prostitutes' arrests and

[9] A substantially different question is whether this mechanism occurs because prostitutes in a certain age group exit prostitution (i.e., a stock effect) or because "potential" prostitutes, in a younger age group, prefer not to enter prostitution (i.e., an inflow effect). I investigate this issue in Appendix Section C.

[10] In Appendix Section, D I provide a complete list of offenses recorded in this database.

the county population for the time period 1980-2014 (except 1984).[11] Appendix Section E presents detailed descriptive statistics of this data set.

3.2 Divorce laws

When coding unilateral divorce laws, two important decisions must be made: (i) whether to use the enactment date or the effective date of the law and (ii) how to classify different unilateral divorce laws. Regarding (i), the enactment date is the date on which a law is approved, while the effective date is the date on which a law enters into effect. I use the effective date since this is when unilateral divorce petitions begin to be filed. It could be that some divorce petitioners anticipated this change since the law was already approved. However, they could not be divorced before the effective date.[12]

Regarding (ii), I focus on unilateral divorce laws without separation requirements to compare identical laws. It is difficult to compare unilateral divorce laws with and without separation requirements since the length of the required separation differs across states. Thus, using unilateral divorce laws with separation requirements would require establishing criteria to compare (i) states with unilateral divorce laws without separation requirements with states with unilateral divorce laws with separation requirements and (ii) states with unilateral divorce laws with separation requirements of different lengths. Since any of such criteria would be subjective, I prefer to focus on unilateral divorce laws without separation requirements. Column (2) of Table 1 displays those states with unilateral divorce laws that required separation of spouses (Cáceres-Delpiano and Giolito 2012).

Therefore, my main explanatory variable in the regression models estimated throughout the paper is a step dummy variable taking value 1 starting in the effective month of the unilateral divorce law in a given state and taking value 0 previous to that date. This variable was constructed by updating Gruber (2004)'s data. As shown in Table 1, during my sample period, six states experienced a change in divorce law.

In addition, for comparability with unilateral divorce laws, I constructed a data set for the dates of entry into force of no-fault divorce laws.[13] After reviewing the literature,

[11] Note that using such data at the agency level does not affect the results.

[12] There can be a lag of at most one year between the enactment date and the effective date. Furthermore, the effective date might be postponed, rendering the enactment date even less important. For further details about using effective dates instead of enactment dates, see Vlosky and Monroe (2002). It is important to use an objective criterion to classify these laws since it could impact my identification assumption and findings, although in this setting, intuitively, it does not appear plausible that the effect is immediate; thus, using either of the two dates should not considerably affect the results.

[13] Coding these laws involves the problems discussed in Appendix Section A.

Vlosky and Monroe (2002) suggest a decision criterion to code no-fault divorce laws that consists of four rules. Rule 1: In states where there is only a no-fault law, use the effective date of that law. Rule 2: In states where no-fault provision/s was/were added to traditional fault divorce law, use the effective date of such provision/s. Rule 3: Use the effective date for the law allowing the shortest separation period. Rule 4: Laws with explicit no-fault provisions supplant laws with no-fault *separate and apart* provisions.[14] I follow their coding of no-fault divorce laws' effective date and again restrict my attention to laws without separation requirements (i.e., Rules 1 and 2).[15]

3.3 Supplementary data sets used

In addition to the data sets described above, I make use of information about arrests for other crimes other than prostitution, the number of police officers hired in each state, and proxies for both demand and supply of prostitution. Data on other crimes are drawn from the agency-level UCR database, which allows me to compute crime rates at the county level.

In this paper, I use "The Police Employee" data set to measure the number of officers per state population. This data set contains annually collected data on law enforcement officers and civilians employed by police departments and their respective rates per location's population from 1971 to 2016.[16] The UCR Program defines law enforcement officers *as individuals who ordinarily carry a firearm and a badge, have full arrest powers, and are paid from governmental funds set aside specifically for sworn law enforcement representatives*. By contrast, civilian employees include personnel such as clerks, radio dispatchers, meter attendants, stenographers, jailers, corrections officers, and mechanics provided that they are full-time employees of the agency. In addition, the totals given for sworn officers comprise not only the patrol officers on the street but also the officers assigned to various other duties such as administrative and investigative positions and special teams.

As a proxy for the demand for prostitution, I use data on searches of words connected to the demand for prostitution on Google.com that are drawn from Google Trends. Since those records are geo-located, I collect the counts for the number of times each word was searched for on Google.com for each county and month in the U.S. These data span from 2004 to 2017.

[14] See Table 2 and Table 3 of Vlosky and Monroe (2002) for further information.

[15] Appendix Section F presents further information about the classification followed to code unilateral divorce laws across U.S. states.

[16] The year 1972 is missing, although there is no reason to believe it is missing due to any special pattern of hired officers.

Another data set used in this respect refers to divorcees' opinions about prostitution and is drawn from a longitudinal survey, precisely from the 1st, 2nd, 3rd and 4th waves of the Youth Parent Socialization Survey (YPSS). This survey was designed to study political socialization and was implemented by the Survey Research Center and Center for Political Studies of the University of Michigan. This study started in 1965 and collected data in three other different waves that took place in 1973, 1982 and 1997. There is a total of 934 respondents (458 men and 476 women) in the four waves. These data are also available from the ICPSR web-page.

Since the YPSS data contain information on the marital status of their respondents, it is known whether an individual who was previously married was divorced during the subsequent waves. Further, this survey collected information on topics that respondents disliked.[17] Replies were classified into multiple categories, one of which was prostitution.[18]

The last database is the monthly Current Population Survey (CPS), which is an employment-focused cross-sectional survey. The U.S. Census Bureau of Labor and Statistics administers the CPS monthly to approximately 60,000 U.S. households. The survey collects information on a number of variables connected to the employment status of each household member aged 15 years or older. Such information is provided by an adult member of the household. A multistage stratified statistical sampling scheme selects sample households. Such households are surveyed for 4 consecutive months, interviews are halted for 8 months, and households are eventually are resurveyed for 4 additional months. The sample represents the civilian non-institutional population. The CPS data used in this paper extend from 1980 to 2014.[19]

4 Estimation approach and main results

In this section, I explore the causal effect of unilateral divorce laws on the arrests of female prostitutes. First, I present my identification strategy that exploits reasonable exogenous variation in the time at which unilateral divorce laws became effective across U.S. states. Next, I discuss my econometric specification in detail. Finally, I report the main empirical results uncovered by the regressions.

[17]Namely, the survey inquires into topics respondents were "least proud of".

[18]The survey question is as follows: "What are the things you are least proud of as an American"? The answer connected to prostitution states: "Immorality in general; low morals; deterioration in moral standards; also specific actions--e.g. drinking, gambling, overexposure; lewdness in behavior or in mass media or literature; pornography, prostitution".

[19]The CPS data used in this paper are drawn from the Uniform Extracts of the CPS ORG. Center for Economic and Policy Research. 2017. CPS ORG Uniform Extracts, Version 2.2.1. Washington, DC.

4.1 Identification assumption and regression model

The results of this paper rely on the identification assumption that the months in which unilateral divorce laws became effective in the six states treated during my sample period were not chosen due to any reason related to crime in general or prostitution in particular. However, this concern can easily be dismissed since, to the best of my knowledge, there is no historical evidence that crime rates might have affected such effective dates.

Knowledge of the legislative background is crucial to assessing the credibility of the identification assumption. As I explain in Appendix Section A, "The Divorce Revolution" was caused mainly by the inadequacy of traditional divorce laws and was driven by an apolitical consensus among both liberals and conservatives. Fault grounds and mutual agreement encouraged couples to even perjure themselves and falsify evidence to obtain a divorce. The introduction of divorce laws, it was believed, would reduce perjury by eliminating either mutual consensus, fault grounds or both. Moreover, conservatives supported divorce since they saw it as an widening of personal rights, whereas liberals backed it to prevent women from being locked into dismal marriages.

Another potential concern is that there could be an omitted variable simultaneously affecting the effective date of unilateral divorce laws and female prostitutes' arrests. For example, it could be that the women's rights movement affected both variables. However, this possibility again seems unlikely for two reasons. First, historically, women's rights movements were in favor of unilateral divorce but did not have a clear position on prostitution: feminists had and have views both against and in favor of prostitution. Therefore, it does not seem likely that the women's right movement fostering the "The Divorce Revolution" played any role in prostitution regulation. Second, despite "The Divorce Revolution," there has not yet been a "Prostitution Revolution" or any other movement that has systematically changed prostitution laws.[20]

A final concern regarding my identification assumption is the displacement of female prostitutes, clients or police officers among different states. These issues should be analyzed carefully since they could violate the stable unit treatment value assumption (SUTVA). However, I found no evidence or any plausible reason suggesting that prostitutes, clients or police officers moved across states based on their divorce regimes.[21]

[20]Currently, the only state in the U.S. that has legalized prostitution is Nevada. Nevada introduced unilateral divorce laws and legalized prostitution in different years: unilateral divorce law became effective in 1967, while prostitution was legalized in 1971.

[21]Since this paper finds that unilateral divorce decreases prostitution by improving prostitutes' outside options, a possible concern could be that the entry into force of unilateral divorce could cause prostitutes from surrounding states to move to that state to exit prostitution. However, I did not find any evidence

Using data at the county level increases precision and improves comparability across treated and control units. It is more reasonable to compare smaller geographical units, such as counties, than states as a whole. In addition, if my specification were at the year level, the identification assumption would be less plausible. Indeed, it seems likely that other progressive social policies might have become effective in the same year in which unilateral divorce entered into force. If this occurred systematically across the treated states, my estimates might be capturing the joint effect of both unilateral divorce and other progressive laws. However, it is much less likely that such changes in social policies occurred exactly in the same month in which unilateral divorce law became effective.

Specifically, the identification assumption in this paper corresponds to the parallel trends hypothesis in the DiD estimation approach. In other words, the only difference among treated and control counties is that the former were treated. If they had not been treated, they would have experienced the same evolution as the control counties.

This paper considers two control groups: those never treated and those treated before 1980. In fact, since this study makes use of data spanning from 1980 to 2014, whereas many U.S. states promulgated unilateral divorce laws before 1980, I proceed to include such states in the control group.

In particular, the following regression model is considered here:

$$log(1 + Prost_{csmy}) = \beta Unilat_{smy} + \alpha_m + \alpha_y + \alpha_c + \alpha_c * y + \varepsilon_{csmy} \quad (1)$$

where $Prost_{csmy}$ is the number of arrests of female prostitutes per 1,000,000 inhabitants in county c of state s in month m of year y.[22] α_m, α_y, α_c, are month, year and county fixed effects, respectively; $\alpha_c * y$ is a county-year linear trend; $Unilat_{smy}$ is the main regressor of interest, namely, a dummy variable taking value 0 before the effective month of unilateral divorce and value 1 in the month in which the unilateral divorce law becomes effective and afterwards. For states that were treated before 1980, $Unilat_{smy}$ always takes value 1; however, for states that were treated after 2014 or have never been treated, $Unilat_{smy}$ takes value 0.

Taking the logarithmic transformation of the dependent variable is common in crime economics, mainly because the data present extreme values that may skew the results. In addition, since arrests might take value 0, I use $log(1 + Prost_{csmy})$ as the dependent

supporting this hypothesis.

[22] Arrests of female prostitutes per 1,000,000 inhabitants are computed as the number of arrested female prostitutes divided by population and multiplied by 1,000,000. The same computations are made for data on other crimes in the rest of this paper.

variable.

Note that the specification considered in this paper is quite demanding since it takes into account that crime patterns respond to seasonal changes (via the inclusion of month fixed effects) and that these patterns might differ among counties within the same state (via inclusion of county fixed effects and county-year trends). Moreover, as a robustness check, I also check whether my findings are robust to the inclusion of year-month fixed effects.

4.2 Results

Panel A of Table 2 shows the results of estimating model (1). Columns (1) and (2) include county-year trends and county fixed effects; column (1) clusters variance at the county level, while column (2) clusters variance at the state level. In both columns, the estimated coefficient is significantly negative at standard significance levels. In column (3), I add year fixed effects; in column (3), I introduce month fixed effects; and in column (4), I add year-month fixed effects. In columns (1) and (2), the estimated coefficient is significantly negative at the 1% and 5% levels, respectively. Moreover, the estimated coefficient is robust to the inclusion of seasonal fixed effects. In fact, after adding year and month fixed effects, in columns (3) and (4), the estimated coefficient is similar in size and significantly different from zero at the 10% level. There could be concerns regarding the level of significance of these results, and hence, for ease of comparison, Table 2 reports the p-values associated with the null of zero effect for each estimated coefficient. It is reassuring that such p-values range between 0.046 and 0.055. In particular, note that the significance of my results is not affected by the inclusion of year-month fixed effects (i.e., column (5)).

After simple back-of-the-envelope computations, the coefficient estimates in column (3) indicate that unilateral divorce laws decrease the arrests of female prostitutes by roughly 10%.[23] Since in my data set, on average, approximately 60,000 female prostitutes are arrested each year in the U.S., this finding implies that the introduction of unilateral divorce could cause a decrease of 6,000 women being arrested for prostitution in the whole country. According to HG.org (2017)'s estimates, this decrease could yield a reduction in costs of approximately $15 million for American taxpayers.[24] The size of this effect could be

[23]These computations simply take into account the structure of my dependent variable to compare it to a standard log-level specification. Precisely, $\frac{\partial \log(y)}{\partial x} = \frac{\partial \log(1+y)}{\partial x} \frac{\partial \log(y)}{\partial \log(1+y)} = \beta \frac{1+y}{y} \simeq \hat{\beta} \frac{1+\bar{y}}{\bar{y}} = -6.8\% \frac{1+1.9}{1.9} = -10.4\%$

[24]According to HG.org (2017), 80,000 arrests cost $200 million. Thus, 60,000 cost $150 million to the taxpayers and a decrease of 10% implies a decrease of $15 million. At the state level, on average, such a

compared to the results presented by Allard and Herbon (2003), who found that prostitution arrests in 2001 caused an expense of $10.3 million in the city of Chicago alone. Therefore, the introduction of unilateral divorce would help the U.S. to save approximately 1.5 times the cost of arrests for prostitutes in Chicago.

It is not straightforward to link these findings to the number of prostitutes based on arrests for female prostitution. According to Fondation-Scelles (2012), there are approximately 1 million female prostitutes in the U.S. Hence, assuming that the observed effect of a 10% reduction in arrests of female prostitutes is the same as that for the number of female prostitutes implies that the number of female prostitutes in the U.S. would decrease by 100,000 if unilateral divorce were effective in all states.

My findings rely on the quasinatural experimental design given by the effective month of unilateral divorce laws across U.S. states, but since my dependent variable spans from 1980 onward, my identifying variation comes from only six states and not from all the adopting states. Thus, there might be the concern that these six states could have had a specific reaction to the event. However, I did not find any evidence or plausible reason to support this hypothesis.

It is important to stress that the external validity of my findings should be interpreted with caution. The prostitution market works differently in developing and developed countries (Farley et al. 2004). Further, unilateral divorce laws were enacted after a period of discussion in the U.S. that led gradually to full social acceptance of divorce. It would be difficult to extrapolate my results to developing countries and to countries that enforced divorce due to foreign influence without having an internal social movement driving such change.

There are several mechanisms that might explain the reduction in arrests of female prostitutes associated with unilateral divorce laws. These mechanisms range from changes in the number of police officers enforcing the law to shifts in either the demand for or the supply of prostitution. After presenting evidence in favor of my identification assumption (Section 5) and discussing the robustness of the results (Section 6), I thoroughly explore each of these mechanisms in Section 7.

5 Concerns about the identification assumption: event study

To ascertain the plausibility of the identification assumption, this section reports an event study analysis regarding the entry into force of unilateral divorce laws, leveraging the high frequency of the data set. Namely, I group data into periods of 12 months to also

decrease would amount to $300,000.

explore the timing of the effect across years. As usual, the excluded indicator is $t = -1$ one year prior to unilateral divorce becoming effective.

Specifically, I estimate the following regression model:

$$log(1 + Prost_{csmy}) = \sum_{j=-3}^{5} \beta Unilat_{s,m,y+j} + \alpha_m + \alpha_y + \alpha_c + \alpha_c * y + \varepsilon_{csmy} \tag{2}$$

Figure 1 plots the estimated coefficients of this event study. The horizontal axis plots the event time (the number of periods prior and posterior to the change in unilateral divorce law), whereas the vertical axis presents the size of the coefficient measured according to its effect on the dependent variable in the main specification. The solid line in the graph depicts the estimated coefficients, and each coefficient is depicted with its own confidence interval at 90% significance levels (dotted lines).

Figure 1 shows that coefficients prior to the occurrence of the event are positive, with point estimates close to zero and statistically equal to zero, while the coefficients posterior to the occurrence of the event are negative and statistically significant. Moreover, the size of the effect is in line with the DiD coefficient. As a whole, these findings support the identification assumption.

6 Robustness checks

This section addresses the robustness of the results. First, it explores whether these results are robust to changes in the dependent variable. Next, it explores the extent to which these results are sensitive to changes in the main specification.

6.1 Sensitivity to changes in the definition of the dependent variable

The concern might be raised that my findings rest on the chosen transformation of the dependent variable (i.e., $\log(1 + y)$). Thus, in what follows, I consider specifications of the dependent variable to analyze whether the previous results persist. First, I consider the inverse hyperbolic sine transformation. Second, I run a linear probability model. Finally, I consider a specification where the dependent variable is given in levels.

The inverse hyperbolic sine transformation (hereafter, IHS) is an alternative to taking the $log(1 + y)$ for dependent variables that take zero values. The IHS is defined as $\log\left(y + (y^2 + 1)^{\frac{1}{2}}\right)$. Panel B of Table 2 shows the results from running the same regression as in Section 3 but taking the IHS of the dependent variable. As can be observed, the findings using the IHS are similar in both sign and size to the those from the main regression. In fact, after simple back-of-the-envelope computations similar to those for the estimated coefficient of the main regression, the effect estimated by the IHS is -9.2%.[25]

Although the dependent variable is in logs, one might be concerned that the results are driven by extreme observations of the dependent variable. To assess this issue, I replace the dependent variable with a binary variable taking value 1 for every positive value of the dependent variable and 0 otherwise. Panel C of Table 2 shows the results of running a linear probability model (hereafter, LPM). Columns (1) and (2) of the table display the estimated coefficient without year and month fixed effects. Column (1) clusters variance at the county level, while column (2) clusters variance at the state level. As in Panel A of the same table, column (3) adds year fixed effects, column (4) adds month fixed effects and column (5) adds year-month fixed effects. The estimated coefficients are always negative and statistically different from zero at 5% at most. These results suggest that the introduction of unilateral divorce law is associated with a 1.8 percentage point reduction in the probability of arresting a female prostitute.

As a final robustness check, Panel D of Table 2 considers a specification where the dependent variable is in levels (i.e., the number of arrests of female prostitutes per 1,000,000 inhabitants). Columns (1), (2), (3), (4) and (5) of Panel D of Table 2 show that the estimated coefficients are negative and statistically significant. Column (4) considers the full specification, where the estimated coefficient is negative and statistically different from zero at the 10% level. This coefficient is approximately $-.77$. On average, there are roughly 2 female prostitutes arrested per 1,000,000 inhabitants per county and month. Accordingly, the decrease caused by the introduction of unilateral divorce is much larger than that estimated in the other specifications. This might be due to the extreme values of the dependent variable that are not transformed in this specification and drive up the estimated coefficient.

In summary, the evidence presented in this subsection supports a negative causal effect of unilateral divorce on the arrests of female prostitutes, irrespective of the chosen functional form of the dependent variable.

6.2 Sensitivity to model specification changes

Next, I analyze whether the results found in this paper depend on other specification issues, such as the choice of the control group and choice of the treatment. It might be that using only one of the two control groups would substantially change the results of the regression. Further, since no-fault divorce and unilateral divorce reforms took place nearly

[25]Precisely, $\frac{\partial \log(y)}{\partial x} = \frac{\partial IHS(y)}{\partial x}\frac{\partial \log(y)}{\partial IHS(y)} = \beta\frac{\sqrt{1+y^2}}{y} \simeq \widehat{\beta}\frac{\sqrt{1+\bar{y}^2}}{\bar{y}} = 8.1\%\frac{\sqrt{1+(1.9)^2}}{1.9} = -9.2\%$

contemporaneously, it might be that the estimated effect is due to the former instead of the latter.

Table 3 shows the results of running the main regression using only one of the two control groups. The estimated coefficients of these regression models should be interpreted with caution since they are computed using a biased, restricted sample. This exercise is only useful to test whether the estimated coefficient from the main regression is statistically equal to the coefficients from the restricted samples. Column (1) only uses the already-treated control group, whereas column (2) uses the never-treated control group. Both columns show results for the full regression model (i.e., with all the controls used in my main specification). The estimated coefficients are negative in both columns but different from zero only in column (1). More important, in both regressions, the estimated coefficients are not statistically different from the estimated coefficient from the main regression. Such evidence indicates that the two control groups produce similar results.

Regarding no-fault divorce laws, I exploit the effective month of no-fault divorce laws in two different ways. First, I add no-fault divorce as a control variable. Second, I replace the unilateral divorce dates with the no-fault divorce dates. Since no-fault divorce does not need proof of wrongdoing or innocence, researchers have theorized that it does not change the bargaining structure within a relationship (Gruber 2004). However, it reduces bargaining costs and financial penalties. If the observed decline in arrests of female prostitutes is caused by no-fault divorce laws instead of unilateral divorce laws, then using this variable as a control should reduce (in absolute value) the size of the estimated coefficient and its statistical significance. Table 4 displays the estimated coefficients from running the main regression of the paper when adding no-fault divorce dates as a dichotomous control. This control takes value 1 in the month that no-fault divorce law becomes effective and in the following months and value 0 before the effective date.[26] As can be seen in Table 4, the estimated coefficients are not statistically different from those from the main regression.[27] This finding supports the notion that no-fault divorce laws did not play an important role in reducing the arrests of female prostitutes.

Table 5 shows the results of running a specification that replaces the effective month of unilateral divorce laws with the effective month of no-fault divorce laws. There are two insights from this specification. On the one hand, it can be viewed as a double check that no-fault divorce laws are not leading to a reduction in the arrests of female prostitutes. In fact, if this were the case, then the coefficient for months in which no-fault divorce became effective should be negative and significantly different from zero. On the other hand, this

[26]Exactly as the treatment variable (i.e., unilateral divorce law).

[27]The point estimate is even slightly larger in absolute value than that from the main specification.

regression can be seen as a placebo test. If unilateral divorce laws are not causing the decline in the number of arrests of female prostitutes, replacing such dates with almost contemporaneous dates should yield similar results.

As can be seen in Table 5, no-fault divorce laws do not appear to be responsible for the reduction in the number of arrests of female prostitutes. Indeed, the estimated coefficients in columns (1), (2), (3) and (4) are nonsignificant and much smaller in size than those from the main regression.

In sum, the evidence provided above demonstrates the robustness of the main regression to the choice of the control group and to no-fault divorce laws.

7 Potential mechanisms

My main finding thus far is that the introduction of unilateral divorce decreased arrests of female prostitutes in the U.S. Several mechanisms could have led to this decline. This section explores each of them by combining multiple data sets.[28]

First, since the results found in this paper are in line with those of Edlund and Korn (2002), I use a simplified version of their model to analyze the mechanisms at work in my findings. Edlund and Korn (2002) argues that the aggregate demand for prostitution $D(p, n)$ is a function of p, the price of commercial sex, and n, the number of single men, whereas the aggregate supply of prostitution $S(n)$ is simply a function of the number of unmarried (single) women n.[29] Thus, p, n are endogenously determined in the model.

Since, in equilibrium, demand is equal to supply, equating them determines p as a function of n (i.e., $p = p(n)$). However, to compute the equilibrium values of p and n, an additional equation is needed. According to their model, this equation is the non-arbitrage condition that connects the marriage market to the prostitution market: in an interior equilibrium, where there are both married women and prostitutes, revenues from

[28]This section does not explore any mechanism connected with migration. One might be concerned that by making marriage more attractive to women, unilateral divorce laws affect the number of women living in a certain state. If this were the case, the finding of this paper might be explained simply by an increase in the population in treated states. Moreover, this hypothesis would violate SUTVA since treatment in a certain state would affect the outcome in a different state. This mechanism seems unlikely because spouses can file for divorce in a different state from that where they were married as long as one of the spouses meets the residency requirements of that state, so there would not be any incentive to move to a state to marry due to its unilateral divorce law. However, I investigate this issue using, as the dependent variable, data on the number of men and women and the sex ratio in each state. If this mechanism were at work, my treatment variable would affect at least one of the three dependent variables listed above. As expected, I find no empirical evidence supporting this hypothesis. The relevant tables are available from the author upon request.

[29]In their model, there are equal numbers of women and men, and since marriage is monogamous, the number of single men and single women is the same.

the two activities must be equal. As a consequence, p, the wage earned by prostitutes, is equal to w, the wage earned in the labor market by wives, plus the compensation p_m paid in equilibrium to married women by their partners. These two curves (i.e., $p = p(n)$, computed from the equilibrium condition $D(p, n) = S(n)$ and $p = w + p_m$), determine the equilibrium of the prostitution market, as shown in Figure 2.

Hence, according to this simple model, there are two mechanisms related to the prostitution market, and specifically to the supply of prostitution, that might explain the findings of this paper:

- It might be that unilateral divorce increases w, that is, the wage earned by wives.
- It might be that unilateral divorce increases the compensation p_m paid in equilibrium to wives by their husbands.

However, one might be concerned that my findings could be explained by mechanisms not related to the supply of prostitution. Namely, there might be concerns that the reduction in prostitution I observe is due either to crime patterns (I analyze this hypothesis in the *Fight against crime mechanism* subsection) or to the demand for prostitution (I analyze this hypothesis in the *Demand mechanisms* subsection). to this effect, if unilateral divorce law decreases all types of crimes committed by women, then I would find a decrease in female prostitution arrests but this decrease would not be related to prostitution per se. This is the first mechanism this section explores.

7.1 Supply mechanisms

As explained at the beginning of this section, there are two supply mechanisms suggested by Edlund and Korn (2002): wives' wage and marriage compensation. In this subsection I test both of them.

7.1.1 Wives' wage

The non-arbitrage condition between marriage and prostitution in Edlund and Korn (2002) establishes that p, the wage earned by prostitutes, must be equal to w, the wage earned in the labor market by wives, plus p_m, the compensation paid in equilibrium in the marriage market. If the introduction of unilateral divorce increases w, prostitution will decrease in equilibrium.[30] Thus, it seems plausible that since the enactment of unilateral

[30] An alternative mechanism, not supported by the literature, is that unilateral divorce increases women's wages (not only wives' wages). This increase could in turn decrease prostitution insofar as legal jobs become more attractive to women and deter them from prostitution. I also explored this hypothesis and found no evidence in its favor. The relevant tables are available upon request.

divorce bolsters women's rights, it could lead to an increase in wives' wages. An increase in w makes marriage more attractive to women, meaning that some women might prefer to exit prostitution. To test this hypothesis, this subsection makes use of monthly CPS data to compute the average real wage of married women across states in the U.S. I run the following specification:

$$W_{smy} = \beta Unilateral_{smy} + \alpha_m + \alpha_y + \alpha_s + \alpha_s * y + \varepsilon_{smy} \tag{3}$$

where W_{smy} stands for wives' average real wage in state s in month m of year y, while the rest of the terms follow the same notation as in regression models (6) and (8). Column (1) of Table 6 reports the results of this specification using as the dependent variable wives' average real wage in logs, while column (2) reports results for wages in levels. Table 6 shows that the estimated coefficients of these regressions are both close to zero and not statistically different from zero. Specifically, the upper bound of the 90% confidence interval of the regression results reported in column (1) suggests the surge in wives' wages is at most 2.7%. Similarly, the same statistic for the regression reported in column (2), taking into account the sample mean, suggests that the boost in wives' wages is at most 2%. This finding indicates that the decay found in the number of arrests of female prostitutes is not caused by an increase in wives' wages.[31]

7.1.2 Marriage compensation

As discussed in Section 2, an increase in wives' welfare is tantamount to an increase in p_m. If the enactment of a unilateral divorce law increases p_m, following Edlund and Korn (2002), prostitution declines. I refer to this as the marriage compensation mechanism. The compensation p_m paid in equilibrium in the marriage market can be interpreted as the compensation husbands pay (both pecuniary and non-pecuniary) to wives. According to Edlund (2013), p_m is compensation for custodial rights. In other words, traditionally, women are the sole guardians of children for out-of-wedlock births (i.e., births outside marriage), while, within marriage, the guardians of a child are her/his parents. Hence, within marriage, women sell a share of their custodial rights to their husbands, and p_m is what they receive in exchange. Thus, if unilateral divorce increases p_m, the main beneficiaries will be women who can marry and have children, in other words, women who are of marrying and fertile age. To test this hypothesis, I restrict my sample to women who

[31] Note that considering the impact of unilateral divorce on the labor force participation of wives would be uninformative about this (i.e., the wives' wage) mechanism. The labor force participation of wives might rise after the introduction of unilateral divorce due to an improvement in wives' bargaining position within the household.

are of both marrying and fertile age. In my sample period, the median marriage age in the U.S. for women is 24.8 years old.[32] In addition, Alesina and Giuliano (2007) studied the effect of unilateral divorce on fertility and used 49 as the boundary age for women. Accordingly, I restrict the analysis to women between ages of 25 and 49, and I refer to this group as women of marrying-fertile age.[33] If unilateral divorce increases p_m, the reduction in arrests of female prostitutes would be larger (in absolute value) in the marrying-fertile age group than for other age groups. Thus, I estimate the main regression separately for women of marrying-fertile age and of other ages. Edlund and Korn (2002)'s model aside, running this regression also tests whether unilateral divorce has an impact on the supply of prostitution as a whole. If unilateral divorce decreases the supply of prostitution as a whole, without affecting marriage compensation, there is no reason to believe that the effect of this law on prostitution differs across age groups. A comparison of the estimated coefficients for the two groups determines whether the impact of unilateral divorce law across these two age groups differs or is the same. Table 7 shows the results of estimating the main regression for these two samples of women. Columns (1) and (3) show the results using $\log(1+y)$ as the dependent variable, while columns (2) and (4) use the IHS transformation. Comparing columns (1) and (3) and columns (2) and (4), I find that the estimated coefficients for women of marrying-fertile age are much larger (in absolute value) than their counterparts of other ages. It is important not to misinterpret the statistical nonsignificance of the estimated coefficients of the regressions reported in columns (1) to (4) as a lack of evidence supporting the marriage compensation mechanism. This mechanism merely predicts that the effect across prostitutes of marrying-fertile age and other ages is different; it does not hold that it should be significant. Indeed, both a z-test and a system of seemingly unrelated regressions reject the notion that the estimated coefficients should be statistically indistinguishable across columns (1) and (3) (columns (2) and (4)) at standard significance levels.[34] Moreover, a careful comparison between table 7 and table 2 highlights that the lack of statistical significance in the estimates reported in columns (1) and (2) of the former table might be due to statistical imprecision (larger standard errors than those in Panel A of table 2 for regressions in logs and in Panel B of

[32] I computed the median age between 1980 and 2014 for women at first marriage from the U.S. Census Bureau. The median is 24.8 years, and the average is 24.5 years.

[33] The relative size of the two samples is fairly balanced since approximately 60% of my sample falls within the marrying-fertile age range (Table A.3). Moreover, it is important to note that only having data on prostitutes' prices would not be informative to assess the marriage compensation mechanism. A potential threat to this approach is that since according to Edlund et al. (2009), prostitutes' prices are higher for women between 21 and 40 years old, if unilateral divorce law decreases the number of prostitutes of marrying-fertile age due to a rise in p_m, I might find an ebb in average prostitutes' prices simply because some of the prostitutes with the highest prices are exiting the market.

[34] The p-values are available upon request.

the same table for regressions in IHS). However, the lack of significance of the estimates reported in columns (3) and (4) does not derive from such a lack of precision.

To provide a further test to this end (i.e., improve precision), equation (6) presents a regression model that pools all observations but separates the number of arrested prostitutes according to the two previously defined age groups using a dummy variable and its interaction with the treatment. Specifically, I consider the following regression model:

$$log(1+Prost_{acsmy}) = \beta_1 Unilat_{smy} + \beta_2 \alpha_a * Unilat_{smy} + \alpha_a + \alpha_m + \alpha_y + \alpha_c + \alpha_c * y + \varepsilon_{acsmy} \tag{4}$$

The difference with respect to the main specification (i.e., equation (1)) is that this regression model takes into account the age group a of the arrested prostitutes. α_a is a dummy variable taking value 1 if the arrested prostitutes are in the marrying-fertile age group and 0 if they are not. Running this regression allows me to test, using the whole sample, whether unilateral divorce has a different effect according to the age group. Indeed, β_1 captures the effect of the introduction of unilateral divorce on arrested prostitutes not in the marrying-fertile age group, while $\beta_1 + \beta_2$ captures the effect of such a law on arrested prostitutes in the marrying-fertile age group. Hence, testing whether unilateral divorce has a different effect on the arrests of prostitutes in the marrying-fertile age group is equivalent to testing whether β_2 is different from zero. Columns (5) and (6) estimate this regression model using $\log(1 + y)$ and the IHS transformation as the dependent variable, respectively. In both cases, the age fixed effect (i.e., α_a) is positive and statistically significant, indicating that there are more arrests of prostitutes in that age group. Generally, in both regressions, $\hat{\beta}_1$ is negative and statistically indistinguishable from zero, while $\hat{\beta}_2$ is negative and different from zero at the 5% level, indicating that the reduction in the arrested female prostitutes is larger (in absolute value) in the marrying-fertile age group.[35] Next, I consider equation (2) for these two age groups. If the reduction in the number of arrested prostitutes in the marrying-fertile age group is larger than the reduction in other ages, the event study analysis will highlight it. With this aim in mind, figures 3 and 4 show the results of the event study for the marrying-fertile age group and other ages, respectively. The results are clear and aligned with the marriage compensation mechanism: the effect of unilateral divorce on the marrying-fertile age group is larger in absolute value. One possible concern here is that these findings are driven by the in-

[35]In addition, Appendix Section G.2 replicates this analysis for indoor prostitution. The results do not change. It could be argued that the model developed in Edlund and Korn (2002) is better suited to indoor prostitution than street prostitution. Thus, finding empirical evidence in favor of the same mechanism for indoor prostitution is reassuring.

clusion of arrested prostitutes older than 49 years in the comparison group (i.e., in the group "Other ages"). To this extent, Appendix Section G.1 replicates the analysis using only arrested prostitutes between 17 and 24 years of age in the comparison group. The results do not change. The empirical evidence explored in this subsection suggests that I cannot reject the marriage compensation mechanism. In other words, there is empirical evidence consistent with the hypothesis that unilateral divorce reduced prostitution arrests because this law improved wives' welfare. An important strand of the literature is in line with this empirical evidence. Stevenson and Wolfers (2006) find that unilateral divorce decreases female suicides, the number of women murdered by their partners and domestic violence. According to Stevenson and Wolfers (2006), unilateral divorce transfers bargaining power toward the abused spouse, potentially halting mistreatment in extant relationships. As the abused spouse is usually the wife, this channel implies an increase in wives' welfare and consequently a rise in p_m. Alesina and Giuliano (2007) suggest that unilateral divorce makes marriage more attractive since the exit option is easier. According to these authors, unilateral divorce makes people feel less locked into marriages, so women (even women planning child bearing) are more likely to accept marriage. Alesina and Giuliano (2007) find that unilateral divorce decreases both out-of-wedlock fertility and never-married women, while it does not affect in-wedlock fertility. Thereby, the total fertility rate declines. In other words, with an easier "exit option," shotgun marriages become less threatening. Such results are consistent with my findings in two ways. First, these results are in line with an increase in p_m since they offer empirical evidence that unilateral divorce makes marriage more attractive to women because "exiting it" is easier. Second, a share of the decrease in never-married women could be explained by the decrease in the number of female prostitutes caused by this law. Finally, it might seem informative to check whether unilateral divorce increased marriages. However, this would not offer conclusive evidence on the marriage compensation mechanism. The number of marriages is a composite result of the decisions of men and women of different backgrounds. On the one hand, unilateral divorce might have increased marriages for potential prostitutes but decreased them for individuals from a different background, making the sign of the total effect unclear. On the other hand, given the central assumption that prostitution compromises female marriage market prospects, unilateral divorce might lead women not to enter prostitution to avoid compromising such prospects; however, this does not imply that they will eventually marry.

7.2 Fight against crime mechanism

This subsection explores whether the decrease in arrested female prostitutes is related to a general decrease in arrests. There are many factors that could cause a general decrease in arrests. For instance, it might be that in the same month in which unilateral divorce becomes effective in a certain state, the number of police officers decreases in the majority of counties in that state.[36] This seems unlikely since police officers are hired annually, while unilateral divorce laws might become effective in any month of the year; however, it could be an explanation for the results of the paper.[37]

To test whether unilateral divorce affects officers, I estimate a specification where the dependent variable is the number of officers. Namely, since this data set is at the state-year level, I consider the following regression model:

$$Officers_{sy} = \beta Unilateral_{sy} + \alpha_y + \alpha_s + \alpha_s * y + \varepsilon_{sy} \tag{5}$$

where $Officers_{sy}$ is the number of officers per 1,000 inhabitants in state s and year y and the rest of the variables follow the same nomenclature as in the main regression. This regression model captures any change in the number of officers due to the entry into force of unilateral divorce at the state-year level. For example, if, systematically, in the same year unilateral divorce laws become effective the number of police officers hired decreases (increases), then we would expect β to be negative (positive). Table 8 displays the results of estimating specification (2). Columns (1) to (4) show the results when using the dependent variable in levels; columns (5) to (8) use the dependent variable in logs. Columns (1) and (2) present the results for the sample period from 1971 to 2016 without and with state-year trends, respectively. Columns (5) and (6) present results for this same regression but using the dependent variable in logs. Across these four specifications, the estimated coefficient changes sign, is small in absolute value and is not statistically significant in any of them.

Since this data set spans from 1971 to 2016 but my main specification considers the period from 1980 to 2014, one could be concerned that unilateral divorce decreases the number of officers only during my sample period. To address this, I also estimate specification (2) using the same sample period as in the main specification. Columns (3) and (4)

[36] A possible explanation is that states where unilateral divorce law becomes effective also reduce police budgets. Note that this event would threaten my identification assumption if it occurs contemporaneously with the entry into force of unilateral divorce.

[37] There are alternative potential mechanisms involving police officers to explain the findings of the paper. For instance, it could be that, contemporaneously with the introduction of unilateral divorce in a certain state, police officers become less strict in arresting criminals or decrease their working hours. Even if implausible, these mechanisms would be able to explain the findings of this paper.

show the results of estimating specification (2) in levels, using the restricted sample between the years 1980 and 2014, without and with state-year trends, respectively. Columns (7) and (8) repeat this analysis but with the dependent variable in logs. Again in this case, the estimated coefficient changes sign depending on the specification of the dependent variable, and, more important, it is small in absolute value and statistically nonsignificant in all regressions.

On the whole, I do not find any empirical evidence supporting the notion that unilateral divorce has an impact on the number of officers. Furthermore, the lower bound of the 90% confidence interval of the main regression in Table 8 (Column (8)) indicates that the reduction in the number of officers is at most 2.6%. Hence, specifically, I do not find evidence that unilateral divorce decreases the number of police officers.[38]

Another potential mechanism is that unilateral divorce could decrease all types of crimes committed by women. If this were true, the observed decline in arrests of female prostitutes could be explained by a general reduction in crimes committed by women. If unilateral divorce laws did not affect either police officers' behavior or crimes committed by women, running a regression with women arrested for crimes other than prostitution would yield estimated coefficients that are statistically equal to zero.

To test this hypothesis, I consider a specification similar to the main regression but where I change the dependent variable. I use three different dependent variables: women arrested for robberies, vandalism and drug crimes/usage.[39] If unilateral divorce laws are shaping police officers' behavior or decreasing their number, then I should observe a decrease for these crimes as well. In fact, robberies, vandalism and drug crimes occur more frequently than prostitution and are easier to catch; therefore, if either police's behavior or women's crime behavior are changing, these crimes would also change.[40]

[38] Appendix Section I.1 presents the results of the same analysis using the yearly change in (i.e., first difference of) the number of officers per 1,000 inhabitants and the growth rate of the number of officers per 1,000 inhabitants as the dependent variables. Again, I find no evidence supporting this mechanism.

[39] This regression analysis has two main features. First, it uses crimes committed only by women since unilateral divorce might change men's behavior. Indeed, assuming that, on average, male incarceration decreases the likelihood that women marry (Charles and Luoh 2010) and that, on average, women (i.e., wives) used to own less resources than men (i.e., husbands) implies that the introduction of unilateral divorce should decrease crimes committed by men by increasing wives' bargaining power (w.r.t. mutual consent divorce). As a consequence, using crimes committed by men would be uninformative for studying the aforementioned mechanism. Second, this analysis makes use only of crimes not connected to prostitution since crimes related to prostitution (e.g., rape, sexual offenses, loitering, homicides) could be affected by unilateral divorce and not via a general decrease in arrests (Urban Justice Center 2005; Cunningham et al. 2017; HG.org 2017).

[40] Therefore, there is no reason to believe that a lack of statistical significance in the regression results might be due to low precision of the estimates, as this was not the case for a much rarer crime such as prostitution. In addition, Appendix Section I.2 presents results for each of the main categories of offenses recorded by UCR. The findings do not change.

Table 9 shows the results of estimating my main regression using data on women arrested for such crimes. Columns (1), (3) and (5) show the results using as the dependent variable $\log(1+y)$, while columns (2), (4) and (6) repeat these computations for the IHS of the dependent variable. Regarding robberies, the estimated coefficients are statistically equal to zero with point estimates close to zero for both regressions. Regarding drug crimes, the estimated coefficients are also statistically nonsignificant but larger in absolute value for both $\log(1+y)$ and IHS. Finally, for vandalism, the two estimated coefficients are positive and not statistically different from zero.

As a whole, the empirical evidence explored in this section suggests that unilateral divorce laws do not have an effect on arrests or crimes generally but, rather, on prostitution specifically. Therefore, according to these findings, the reduction in the number of arrested prostitutes caused by unilateral divorce cannot be explained by a general decrease in arrests or crimes.

7.3 Demand mechanisms

The estimated reduction in the arrests for female prostitution might be driven by a decrease of the demand for prostitution. Indeed, there are many mechanisms through which unilateral divorce could shift the demand for prostitution. For example, Edlund and Korn (2002) assume that unmarried men demand more prostitution than married men. Thus, by increasing the number of male divorcees and, as a result, the number of single men, unilateral divorce may lead to a rise in the demand for prostitution. Another example is that unilateral divorce laws change people's attitudes, in turn driving up the demand for prostitution.

In the sequel, I test whether this mechanism is supported by the data using three different data sets that proxy for different features of the demand for prostitution.[41]

7.3.1 Internet searches

The first data set used is drawn from Google Trends. Cunningham and Kendall (2010, 2011c, 2013) contend that "overall, online solicitation represents an augmentation of the prostitution market".[42] Indeed, according to these researchers, the advent of the internet has allowed prostitutes to (i) more easily reach a larger pool of potential clients, (ii) build reputations for their services and (iii) use screening to filter out unwanted clients.

[41] In addition, Appendix Section J explores a supplementary demand mechanism connected to Edlund and Korn (2002).

[42] Dank et al. (2014) also highlight the expansion of internet use to match clients and prostitutes.

Therefore, using Google Trends, I gather data on searches for different words that might be used by prostitutes' potential clients. The frequency with which these words are searched online might proxy for the demand for prostitution. First, I consider different synonyms of "prostitute". Second, I consider the word "sex". Next, I consider words connected to indoor prostitution such as "stripper", "strip club" and "escort". Finally, I consider words connected to websites known for matching customers and prostitutes.[43] The Erotic Review is one of the most important websites that matches prostitutes and clients in the U.S.[44] It seems plausible that if the demand for prostitution exhibited a change in those years, the searches for such words should have also changed.

Since the Google Trends data set is at the state-month level, in this case, the regression is also estimated at that level. Then, I run the following regression:

$$Searches_{smy} = \beta Unilateral_{smy} + \alpha_m + \alpha_y + \alpha_s + \alpha_s * y + \varepsilon_{smy} \quad (6)$$

where $Searches_{smy}$ stands for the number of searches for a certain word in state s, month m and year y; α_m, α_y and α_s are month, year and state fixed effects, respectively; and $\alpha_s * y$ is a state-year linear trend. If unilateral divorce increases (decreases) the demand for prostitution, the estimated coefficient should be positive (negative) and significant.

Google Trends data are available since 2004. Table 10 displays the estimated coefficients after running such regressions for the largest sample I have (i.e., 2004 to 2017). While Table 11 displays the estimated coefficients after running such regressions until 2014 to partially match the sample period of my main regression, Panels A, B and C show the results in levels, logs and IHS, respectively.[45]

There is no statistical evidence supporting the notion that unilateral divorce might reduce the demand for prostitution. In fact, when considering words not connected to websites that match customers and prostitutes, the estimated coefficients change signs across regressions in both tables, and none is statistically negative. Regarding words connected to the aforementioned websites, the only coefficient statistically different from zero is that for "Backpage Erotic". In both tables 10 and 11, this coefficient indicates that

[43]Namely, "The Erotic Review", "Erotic Review" (easier and faster version to search on Google), "Craigslist", "Backpage" and "Backpage erotic". I cannot consider "Craigslist erotic" since it was not searched in Google enough times (i.e., it was searched so rarely that Google does not index the number of searches).

[44]This website has been used in the literature to collect data on prostitutes and customers (see, among others, Cunningham and Shah (2017)).

[45]The sample size varies across columns since Google Trends data are available only for states where the number of searches is not close to zero. Searches for certain words were close to zero in some states. However, this was not the case for any treated state. A list of missing state/s for each word is available upon request.

unilateral divorce increases searches for such websites. Overall, these findings suggest that unilateral divorce does not reduce the demand for prostitution.

7.3.2 Preferences of divorced men

Unilateral divorce law might indirectly affect the demand for prostitution. For example, it could be that it is the act of being divorced, instead of unilateral divorce law *per se*, that affects people's attitudes.

To study this instance, I use data from the Youth Parent Socialization Survey (YPSS). This survey started in 1965 and had three other waves: 1973, 1982 and 1997. Since the YPSS followed individuals during these three waves, by using these data, it is possible to study how the observable characteristics of divorced people changed after their divorces.[46]

In particular, to proxy for the demand for prostitution, I use changes in the opinions of male respondents about prostitution. This survey measures the dislike of their respondents toward various issues, one of which is prostitution. Consequently, I can observe whether, after being divorced, men report that they dislike prostitution more or less often than before. It seems reasonable to assume that higher levels of dislike of prostitution among male respondents might lead to reduced demand for prostitution, which could explain the findings of this paper.

I run the following regression model:

$$Dislike\,Prostitution_{iw} = \beta_1 divorced_{iw} + \beta_2 divorced_{iw} * male_i + X_{iw}\delta + \alpha_i + \alpha_w + \varepsilon_{iw} \quad (7)$$

where $Dislike\,Prostitution_{iw}$ is a dummy variable taking value 1 if respondent i expresses dislike of prostitution in survey wave w, X_{iw} is a vector of characteristics that includes the sex of the respondent and marital status in wave w of the survey and α_i, α_w are individual and wave fixed effects, respectively. Finally, $divorced_{iw}$ is a dichotomous variable that takes value 1 if individual i was divorced in wave w of the survey. In addition, standard errors are clustered at the school code level.

This regression exploits the variation in being divorced across successive waves of the survey for a given individual to compute the correlation between divorced males and their aversion to prostitution. Namely, a positive β_1 implies that marital dissolution, for both men and women, correlates with aversion to prostitution. Similarly, a positive β_2 implies that divorced men are more likely to dislike prostitution.

[46]This data set has been used by Edlund and Pande (2002) to show that, after being divorced, women are more likely to support left-wing parties.

Column (1) of Table 12 shows the results of regression model (7), where $divorced_{iw}$ takes value 1 only for divorced respondents. Both $\hat{\beta}_1$ and $\hat{\beta}_2$ are not statistically significant. However, $\hat{\beta}_2$ is positive, suggesting that divorced men might be more averse to prostitution. To check whether these findings are stable, I run three additional regressions. Column (2) of Table 12 pools respondents whose marital status is divorced or separated (i.e., $divorced_{iw}$ takes value 1 for both divorced and separated respondents). In this specification, $\hat{\beta}_2$ is negative. Furthermore, the size of the standard errors is unchanged, suggesting that the statistical nonsignificance of $\hat{\beta}_2$ is not due to a lack of precision.

Notwithstanding, the previous regressions treat as divorced those individuals who were divorced in wave w of the survey. Hence, the same individual could be divorced in wave w but then married in wave $w + 1$. It is more conservative to consider as divorced (separated) individuals who were divorced (separated) at least once in the surveys. It might even be the case that it is only after the first divorce (separation) that men change their preferences toward prostitution.[47] This could explain the change in sign of $\hat{\beta}_2$ across columns (1) and (2).

Consequently, as a further check, the last two columns of Table 12 (i.e., namely, columns (3) and (4)) consider respondents who claimed to be divorced/separated in a previous wave of the YPSS as divorced and/or separated. As an example, suppose that individual j was divorced in wave 2 and married again in wave 3; column (1) would consider this individual to be divorced in the former and married in the latter, whereas column (3) would consider this individual to be divorced in both periods. Column (4) pools both divorced and separated individuals. Columns (3) and (4) of Table 12 show that across both regressions, $\hat{\beta}_2$ is negative.[48] In addition, in these columns, both $\hat{\beta}_1$ and $\hat{\beta}_2$ are not statistically different from zero, and the size of the standard errors is unchanged, suggesting that the lack of statistical significance is not due to imprecision. Consistently, the upper bound of the 90% confidence interval of the most conservative setting (column(4)) suggests that men who are divorced or separated for the first time are associated with an increased dislike of prostitution at most by 0.7%. This result suggests that being divorced or separated is not negatively associated with attitudes toward prostitution. Overall, these results do not support the notion that being divorced reduces the demand for prostitution.

[47]Note that since the YPSS considers the marital status of respondents in wave w, if this were the case, it would bias my results.

[48]This supports the hypothesis that it is the first divorce (separation) that changes males' attitudes toward prostitution.

7.3.3 Unmarried men

The last dimension in which I test whether unilateral divorce shifts the demand for prostitution uses data on unmarried men. According to Edlund and Korn (2002), unmarried men demand more prostitution than married men. Hence, finding that unilateral divorce is associated with a decrease in unmarried men might be evidence that the demand for prostitution declines, leading to a reduction in arrests of female prostitutes.

To compute the number of unmarried men per state, I use monthly data from the Current Population Survey (CPS) between 1980 and 2014. Therefore, since CPS data are at the state level, I collapse my data set to the state level and run the following regression:

$$Unmarried\,men_{smy} = \beta Unilateral_{smy} + \alpha_m + \alpha_y + \alpha_s + \alpha_s * y + \varepsilon_{smy} \tag{8}$$

where $Unmarried\,men_{smy}$ is either the number of unmarried men per 1,000,000 inhabitants in state s, month m and year y or its growth rate. The other variables follow the same notation as in regression model (6). Columns (1) and (2) of Table 13 show the results when using as the dependent variable the number of unmarried men per 1,000,000 inhabitants and its growth rate, respectively.[49] Column (3) shows the results for the logarithmic transformation of the number of unmarried men per 1,000,000 inhabitants. As Table 13 shows, the estimated coefficients are positive and not statistically different from zero. These findings suggest there is no empirical evidence that unilateral divorce decreases the number of unmarried men. Specifically, column (3) finds that the 90% confidence interval is plausibly consistent with a decline at most 1.3%. These results suggest that unilateral divorce does not reduce the number of unmarried men.[50]

In essence, this subsection does not find any empirical evidence that a unilateral divorce law might cause a decline in the demand for prostitution. Thus, this evidence supports the notion that the decline observed in the number of arrested female prostitutes is not caused by a decrease in the demand for prostitution.

[49] I estimate both regressions since it could be argued that the number of unmarried men does not vary substantially across months.

[50] Note that this result does not contradict the marriage compensation mechanism since according to this mechanism, unilateral divorce improves wives' welfare. First, the effect of unilateral divorce law on the marriage market is a composite effect depending on the effect of the law on other sub-populations (not only on prostitutes). Second, it might be that prostitutes do not enter or exit prostitution in the hope of being married but are not ultimately married.

8 Concluding remarks

This paper empirically explores the economic determinants of female prostitution using a quasinatural experimental setting provided by differences in the timing of entry into force of unilateral divorce laws across U.S. states. Female prostitution is proxied by the arrests of female prostitutes in the absence of any other reliable information on this illegal activity. My main finding is that the introduction of unilateral divorce decreases female prostitution arrests by roughly 10%. This estimate of the causal effect translates into a reduction of approximately 6,000 women arrested for prostitution in the U.S. According to HG.org (2017)'s estimates, this decrease in prostitution arrests yields a reduction of approximately $15 million in costs for American taxpayers.

To explore the credibility of the identification assumption behind this causal effect, I consider an event study analysis in a time window close to the policy intervention. I find conclusive evidence that the causal effect occurs after the law entered into force.

Next, I carefully explore numerous underlying channels that could be driving the results. The explored mechanisms range from changes in police officers' effectiveness in fighting crime to shifts in the demand for and supply of prostitution. To identify the latter, I rely on the well-known model of the link between marriage and prostitution markets proposed by Edlund and Korn (2002).

In line with Edlund and Korn (2002), the overall evidence analyzed in this paper suggests that the main mechanism through which unilateral divorce laws have a causal effect on prostitution is by improving women's compensation when married, which subsequently leads to a reduction in the supply of prostitution. Since the empirical evidence presented above does not yield support for a decline in the demand for prostitution, reduced supply would translate into a smaller amount of prostitution in equilibrium. To the best of my knowledge, this is one of the first papers to show that improving prostitutes' outside options deters prostitution.

Tables & Figures

Table 1: Effective months of entry into force of unilateral divorce laws

	(1)	(2)
Alabama	1971	
Alaska	1935	
Arkansas		
Arizona	1973	
California	1970	
Colorado	1972	
Connecticut	1973	
District of Columbia		1 year 1977
Delaware	1968	
Florida	1971	
Georgia	1973	
Hawaii	1972	
Idaho	1971	
Illinois		2 years, August 1984
Indiana	1973	
Iowa	1970	
Kansas	1969	
Kentucky	1972	
Louisiana		1 year, pre 1968
Maine	1973	
Maryland		5 years; later 2 years pre-1968
Massachusetts	1975	
Michigan	1972	
Minnesota	1974	
Mississippi		
Missouri	September 2009	2 years, 1973
Montana	1973	
Nebraska	1972	
Nevada	1967	
New Hampshire	1971	
New Jersey	January 2007	18 months, 1971
New Mexico	1933	
New York	October 2010	
North Carolina		1 year, pre-1968
North Dakota	1971	
Ohio		1 year, 1974
Oklahoma	1953	
Oregon	1971	
Pennsylvania		3 years, 1980; 2 years, January 1991
Rhode Island	1975	
South Carolina		3 years; later 1 year, 1969
South Dakota	January 1985	
Tennessee		
Texas	1970	
Utah	January 1987	3 years, pre-1968
Vermont		6 months, pre-1968
Virginia		2 years, pre-1968
Washington	1973	
West Virginia	September 2001	2 years; later 1 year, pre-1968
Wisconsin	1978	
Wyoming	1977	

Notes: This table reports the effective month of entry into force of unilateral divorce laws across U.S. states. It reports the effective year for states where unilateral divorce law entered into force prior to 1980, and the effective month for states where unilateral divorce law entered into force during my sample period (i.e., between 1980 and 2014). Column (1) of this table updates Gruber (2004) (without separation requirements), while column (2) updates Cáceres-Delpiano and Giolito (2012) (with separation requirements).

Table 2: Main results

Panel A: Log(1+y)	(1)	(2)	(3)	(4)	(5)
Unilateral	-0.0719***	-0.0719**	-0.0687*	-0.0682*	-0.0685*
	(0.0188)	(0.0351)	(0.0349)	(0.0349)	(0.0349)
	[0.001]	[0.046]	[0.055]	[0.056]	[0.055]
Panel B: IHS	(1)	(2)	(3)	(4)	(5)
Unilateral	-0.0848***	-0.0848**	-0.0814*	-0.0808*	-0.0812*
	(0.0201)	(0.0413)	(0.0411)	(0.0411)	(0.0411)
	[0.001]	[0.046]	[0.053]	[0.055]	[0.054]
Panel C: LPM	(1)	(2)	(3)	(4)	
Unilateral	-0.0179***	-0.0179**	-0.0182**	-0.0181**	-0.0182**
	(0.0042)	(0.0088)	(0.0088)	(0.0088)	(0.0088)
	[0.001]	[0.047]	[0.043]	[0.045]	[0.044]
Panel D: Levels	(1)	(2)	(3)	(4)	(5)
Unilateral	-0.8309***	-0.8309*	-0.7661*	-0.7619*	-0.7699*
	(0.1021)	(0.4209)	(0.4467)	(0.4462)	(0.4473)
	[0.001]	[0.054]	[0.093]	[0.094]	[0.092]
Observations	1,252,282	1,252,282	1,252,282	1,252,282	1,252,282
Clustered variance at County level	✓				
Clustered variance at State level		✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓
County Year Trends	✓	✓	✓	✓	✓
Year FE			✓	✓	
Month FE				✓	
Year-Month FE					✓

Clustered standard errors in parentheses, p values in brackets.
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table displays the estimated coefficients of running specification (1). Data are at the county-month level. Columns (1) and (2) include county fixed-effects and county year trends. Column (3) adds year fixed effects, column (4) adds month fixed effects, and column (5) uses year-month fixed effects. Standard errors are clustered at the county level in column (1) and at the state level in columns (2), (3), (4) and (5). The coefficient of interest is statistically negative in all regressions.

Table 3: Robustness check: different control groups

VARIABLES	(1) Only Already Treated	(2) Only Never Treated
Unilateral	-0.0746**	-0.0535
	(0.0351)	(0.0348)
Observations	904,570	487,728
Clustered variance at State level	✓	✓
County Year Trends	✓	✓
County FE	✓	✓
Year FE	✓	✓
Month FE	✓	✓

Clustered standard errors at state level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table displays the estimated coefficients of running specification (1) using only one of the two control groups. Data are at the county-month level. Standard errors are clustered at the state level. Column (1) is restricted to already treated, while column (2) is restricted to never treated.

Table 4: Robustness check: including the effective month of the no-fault divorce law as control

VARIABLES	(1) Log(1+y)	(2) Log(1+y)	(3) Log(1+y)	(4) Log(1+y)
Unilateral	-0.0736*	-0.0690*	-0.0684*	-0.0689*
	(0.0369)	(0.0364)	(0.0364)	(0.0364)
Observations	1,252,282	1,252,282	1,252,282	1,252,282
Clustered variance at State level	✓	✓	✓	✓
County FE	✓	✓	✓	✓
County Year Trends	✓	✓	✓	✓
Year FE		✓	✓	
Month FE			✓	
Year-Month FE				✓

Clustered standard errors at state level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table displays the estimated coefficients of running specification (1) including no-fault divorce effective month as a control variable. Data are at the county-month level. Standard errors are clustered at the state level. Column (1) includes county fixed effects and county-year trends, column (2) adds year fixed effects, column (3) adds month fixed effects, and column (4) uses year-month fixed effects.

Table 5: Robustness check: using the effective month of no-fault divorce law as treatment

VARIABLES	(1) Log(1+y)	(2) Log(1+y)	(3) Log(1+y)	(4) Log(1+y)
No-Fault	-.00980	-0.0167	-0.0168	-0.0165
	(0.0111)	(0.0129)	(0.0129)	(0.0128)
Observations	1,252,282	1,252,282	1,252,282	1,252,282
Clustered variance at State level	✓	✓	✓	✓
County FE	✓	✓	✓	✓
County Year Trends	✓	✓	✓	✓
Year FE		✓	✓	
Month FE			✓	
Year-Month FE				✓

Clustered standard errors at state level in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: This table displays the estimated coefficients of running specification (1) replacing no-fault divorce effective month as the main regressor (i.e., replacing unilateral divorce with no-fault divorce). Data are at the county-month level. Standard errors are clustered at the state level. Column (1) includes county fixed effects and county-year trends, column (2) adds year fixed effects, column (3) adds month fixed effects, and column (4) uses year-month fixed effects.

Table 6: Potential mechanisms: wives' wage

VARIABLES	(1) Log Average Married Women's Real Wage	(2) Average Married Women's Real Wage
Unilateral	0.000558	-0.0407
	(0.0162)	(0.142)
Observations	20,400	20,400
Clustered variance at State level	✓	✓
State FE	✓	✓
Year FE	✓	✓
Month FE	✓	✓
State Year Trends	✓	✓

Clustered standard errors at state level in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: This table displays the estimated coefficients of running specification (3). Data are at the state-month level. Standard errors are clustered at the state level. Each column of the table uses a different dependent variable. Column (1) uses the average married women's real wage in logs; column (2) uses the average married women's real wage. Each column includes state fixed effects, state-year trends, year fixed effects and month fixed effects.

Table 7: Potential mechanisms: marriage compensation

VARIABLES	(1) Log(1+y) Marrying-Fertile age	(2) IHS Marrying-Fertile age	(3) Log(1+y) Other ages	(4) IHS Other ages	(5) Log(1+y) Joint regression	(6) IHS Joint regression
Unilateral	-0.0739	-0.0880	-0.0174	-0.0227	-0.0286	-0.0348
	(0.0466)	(0.0555)	(0.0158)	(0.0187)	(0.0242)	(0.0287)
Dummy Marrying -Fertile age					0.0813***	0.096***
					(0.0174)	(0.0207)
Unilateral*Dummy Marrying-Fertile age					-0.0402**	-0.0476**
					(0.0183)	(0.0218)
Observations	1,252,282	1,252,282	1,252,282	1,252,282	2,504,564	2,504,564
Clustered variance at State level	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓
County Year Trends	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓

Clustered standard errors at state level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table displays the estimated coefficients of running specification (4) for marrying-fertile age sample and for "other ages" sample. Data are at the county-month level. Standard errors are clustered at the state level. Each column of the table uses a different dependent variable. Column (1) uses $\log(1+y)$ of the marrying-fertile age group, column (2) uses the IHS transformation of the marrying-fertile age group, column (3) uses $\log(1+y)$ of the "other ages" group, and column (4) uses the IHS transformation of the "other ages" group. Columns (5) and (6) show the results of running equation (6).

Table 8: Potential mechanisms: fight against crime mechanism

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					Log	Log	Log	Log
VARIABLES	Officers	Officers	Officers	Officers	Officers	Officers	Officers	Officers
Unilateral	-0.00382	0.0361	-0.0116	-0.0210	0.00713	0.0153	0.0207	0.0166
	(0.0702)	(0.0849)	(0.0846)	(0.0752)	(0.0580)	(0.0762)	(0.0427)	(0.0262)
Observations	2,250	2,250	1,750	1,750	2,250	2,250	1,750	1,750
Clustered variance at State level	✓	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
State Year Trends		✓		✓		✓		✓
Sample	1971-2016	1971-2016	1980-2014	1980-2014	1971-2016	1971-2016	1980-2014	1980-2014

Clustered standard errors at state level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table displays the estimated coefficients of running specification (5). Data are at the state-year level. Standard errors are clustered at the state level. Columns (1) to (4) use the dependent variable in levels; columns (5) to (8) use the dependent variable in logs.

Table 9: Potential mechanisms: fight against crime mechanism

VARIABLES	(1) Log(1+y) Robbery	(2) IHS Robbery	(3) Log(1+y) Drugs	(4) IHS Drugs	(5) Log(1+y) Vandalism	(6) IHS Vandalism
Unilateral	-0.00172	-0.00221	-0.0655	-0.0809	0.0256	0.0277
	(0.00836)	(0.0102)	(0.0906)	(0.102)	(0.0589)	(0.0681)
Observations	1,252,282	1,252,282	1,252,282	1,252,282	1,252,282	1,252,282
Clustered variance at State level	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓
County Year Trends	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓

Clustered standard errors at state level in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: This table displays the estimated coefficients of running specification (1) using female robbery, vandalism and drug arrests as the dependent variables. Data are at the county-month level. Standard errors are clustered at the state level. Columns (1), (3) and (5) use $\log(1+y)$ as the dependent variable, while columns (2), (4) and (6) use the IHS transformation as the dependent variable.

Table 10: Potential mechanisms: demand proxied by Google Trends data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Synonyms of prostitute								Indoor prostitution				Websites			
VARIABLES	Prostitute	Bitch	Call Girl	Whore	Hot babe	Hooker	Hustler	Sex	Stripper	Strip club	Escort	The Erotic Review	Erotic Review	Craiglist	Backpage	Backpage Erotic
Panel A: Levels																
Unilateral	1.548	2.343	-2.319	-0.990	2.811	3.317**	-0.653	0.553	1.114**	3.012	1.029	-1.094	-4.382	0.495	3.525	5.044*
	(1.967)	(2.817)	(2.754)	(1.647)	(2.533)	(1.454)	(0.673)	(1.970)	(0.444)	(3.207)	(2.623)	(4.080)	(5.692)	(6.766)	(6.135)	(2.442)
Panel B: Logs																
Unilateral	0.0661	0.0449	-0.123	-0.00262	0.130***	0.0600	0.00443	0.0120	0.0196	0.0389	0.0261	-0.0528	-0.0669	-0.0514	-0.0648	0.0492
	(0.0594)	(0.0397)	(0.0915)	(0.0776)	(0.0454)	(0.0715)	(0.0531)	(0.0265)	(0.0493)	(0.0835)	(0.0373)	(0.215)	(0.204)	(0.196)	(0.201)	(0.0526)
Panel C: IHS																
Unilateral	0.0641	0.0455	-0.145	-0.00180	0.140**	0.0560	0.00256		0.0179	0.0360	0.0268	-0.0524	-0.0666	-0.0667	-0.104	0.0235
	(0.0712)	(0.0436)	(0.118)	(0.0931)	(0.0627)	(0.0869)	(0.0678)		(0.0629)	(0.0982)	(0.0393)	(0.245)	(0.228)	(0.258)	(0.244)	(0.0700)
Observations	8,262	8,262	7,452	8,262	7,128	8,262	8,262	8,262	8,262	8,262	8,262	7,128	5,994	8,262	8,262	2,430
Clustered variance at State level	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
State Year Trends	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Clustered standard errors at state level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table displays the estimated coefficients of running specification (6). Data are at the state-month level. Standard errors are clustered at the state level. Each column includes state fixed effects, state-year trends, year fixed effects and month fixed effects. Sample: January 2004 to December 2017.

Table 11: Potential mechanisms: demand proxied by Google Trends data, sample 2004-2014

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Synonyms of prostitute								Indoor prostitution				Websites			
VARIABLES	Prostitute	Bitch	Call Girl	Whore	Hot babe	Hooker	Hustler	Sex	Stripper	Strip club	Escort	The Erotic Review	Erotic Review	Craiglist	Backpage	Backpage Erotic
Panel A: Levels																
Unilateral	0.715	2.192***	-1.204	-0.0193	5.390***	1.167	0.880	1.589	0.772	2.527	1.749	-0.466	-4.501	3.638	3.019	8.429***
	(2.360)	(0.807)	(3.036)	(2.210)	(1.778)	(3.396)	(0.919)	(3.102)	(0.662)	(5.095)	(4.379)	(4.820)	(6.735)	(7.269)	(5.430)	(0.710)
Panel B: Logs																
Unilateral	0.0251	0.0709	-0.0843	0.0368	0.181***	0.0444	0.0562	0.0322	0.0314	0.0572	0.0433	-0.0991	-0.105	-0.00573	-0.163	0.00747
	(0.0626)	(0.0460)	(0.0909)	(0.0889)	(0.0347)	(0.0644)	(0.0600)	(0.0409)	(0.0551)	(0.106)	(0.0583)	(0.132)	(0.174)	(0.308)	(0.291)	(0.148)
Panel C: IHS																
Unilateral	0.0641	0.0455	-0.145	-0.00180	0.140**	0.0560	0.00256		0.0179	0.0360	0.0268	-0.0524	-0.0666	-0.0667	-0.104	0.0235
	(0.0712)	(0.0436)	(0.118)	(0.0931)	(0.0627)	(0.0869)	(0.0678)		(0.0629)	(0.0982)	(0.0393)	(0.245)	(0.228)	(0.258)	(0.244)	(0.0700)
Observations	8,262	8,262	7,452	8,262	7,128	8,262	8,262	8,262	8,262	8,262	8,262	7,128	5,994	8,262	8,262	2,430
Clustered variance at State level	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
State Year Trends	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Clustered standard errors at state level in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: This table displays the estimated coefficients of running specification (6). Data are at the state-month level. Standard errors are clustered at the state level. Each column includes state fixed effects, state-year trends, year fixed effects and month fixed effects. Sample: January 2004 to December 2014.

Table 12: Potential mechanisms: demand proxied by YPSS data on opinions

VARIABLES	(1) Dislike Prostitution	(2) Dislike Prostitution	(3) Dislike Prostitution	(4) Dislike Prostitution
Divorced	-0.0174		0.00623	
	(0.0255)		(0.0311)	
Divorced & Male	0.0471		-0.0333	
	(0.0395)		(0.0383)	
Divorced/Separated		0.0305		0.0153
		(0.0280)		(0.0275)
Divorced/Separated & Male		-0.0259		-0.0464
		(0.0319)		(0.0320)
Observations	3,736	3,736	3,736	3,736
Clustered variance at School-code level	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓
Wave FE	✓	✓	✓	✓

Clustered standard errors at state level in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: This table displays the estimated coefficients of running specification (7). Standard errors are clustered at school-code level.

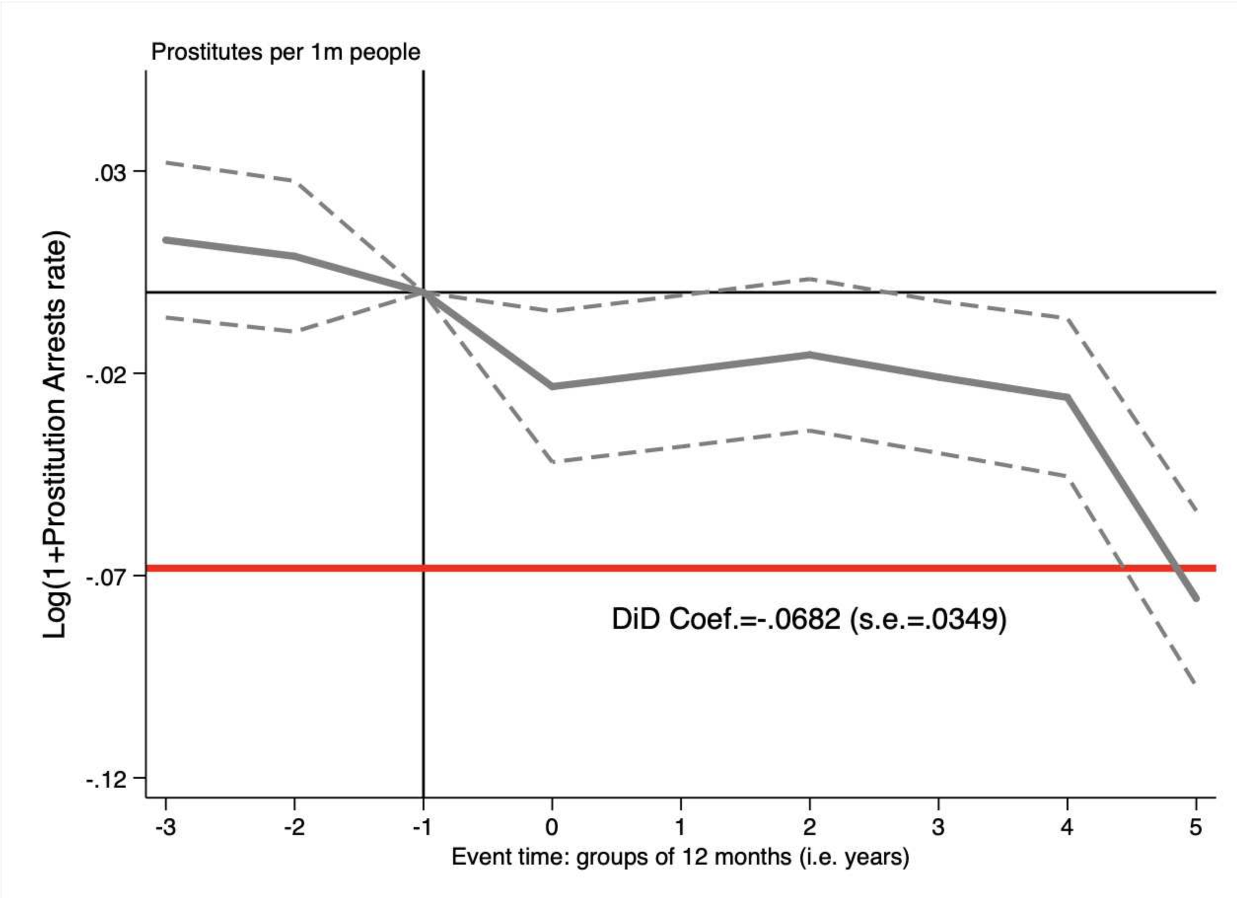
Table 13: Potential mechanisms: demand proxied by number of unmarried men

VARIABLES	(1) Unmarried	(2) Unmarried growth	(3) Unmarried Log(y)
Unilateral	421.7	0.00216	0.0119
	(487.1)	(0.00186)	(0.0149)
Observations	20,400	20,300	20,400
Clustered variance at State level	✓	✓	✓
State FE	✓	✓	✓
Year FE	✓	✓	✓
Month FE	✓	✓	✓
State Year Trends	✓	✓	✓

Clustered standard errors at state level in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

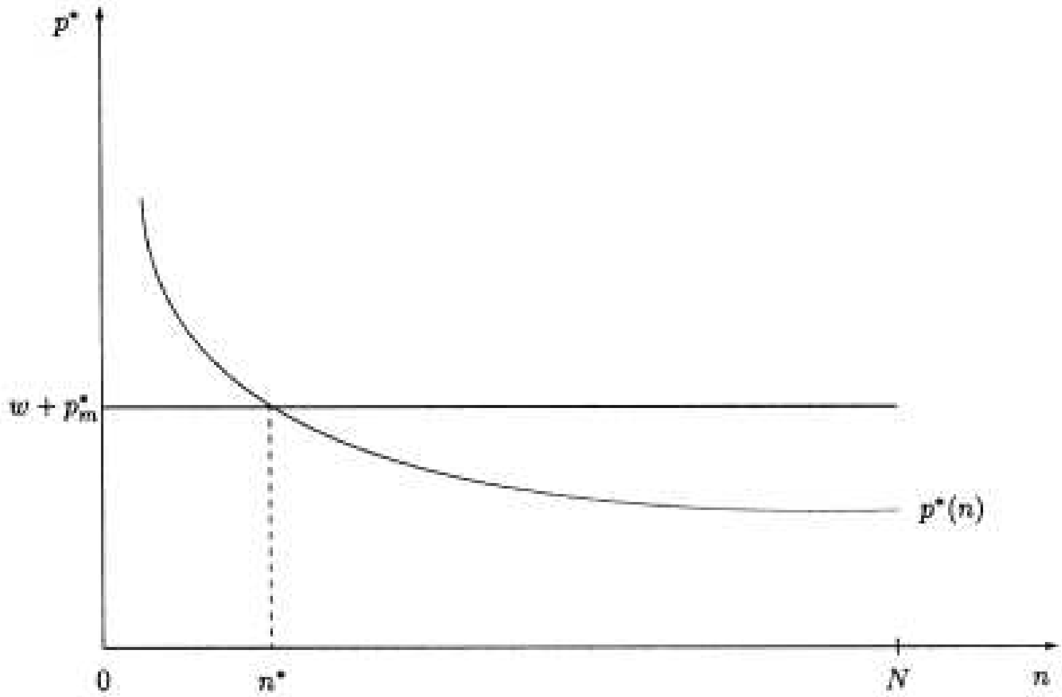
Notes: This table displays the estimated coefficients of running specification (8). Data are at the state-month level. Standard errors are clustered at the state level. Each column of the table uses a different dependent variable. Column (1) uses the number of unmarried men, column (2) uses the growth rate of the number of unmarried men, while column (3) uses the number of unmarried men in logs. Each column includes state fixed effects, state-year trends, year fixed effects and month fixed effects.

Figure 1: Event study



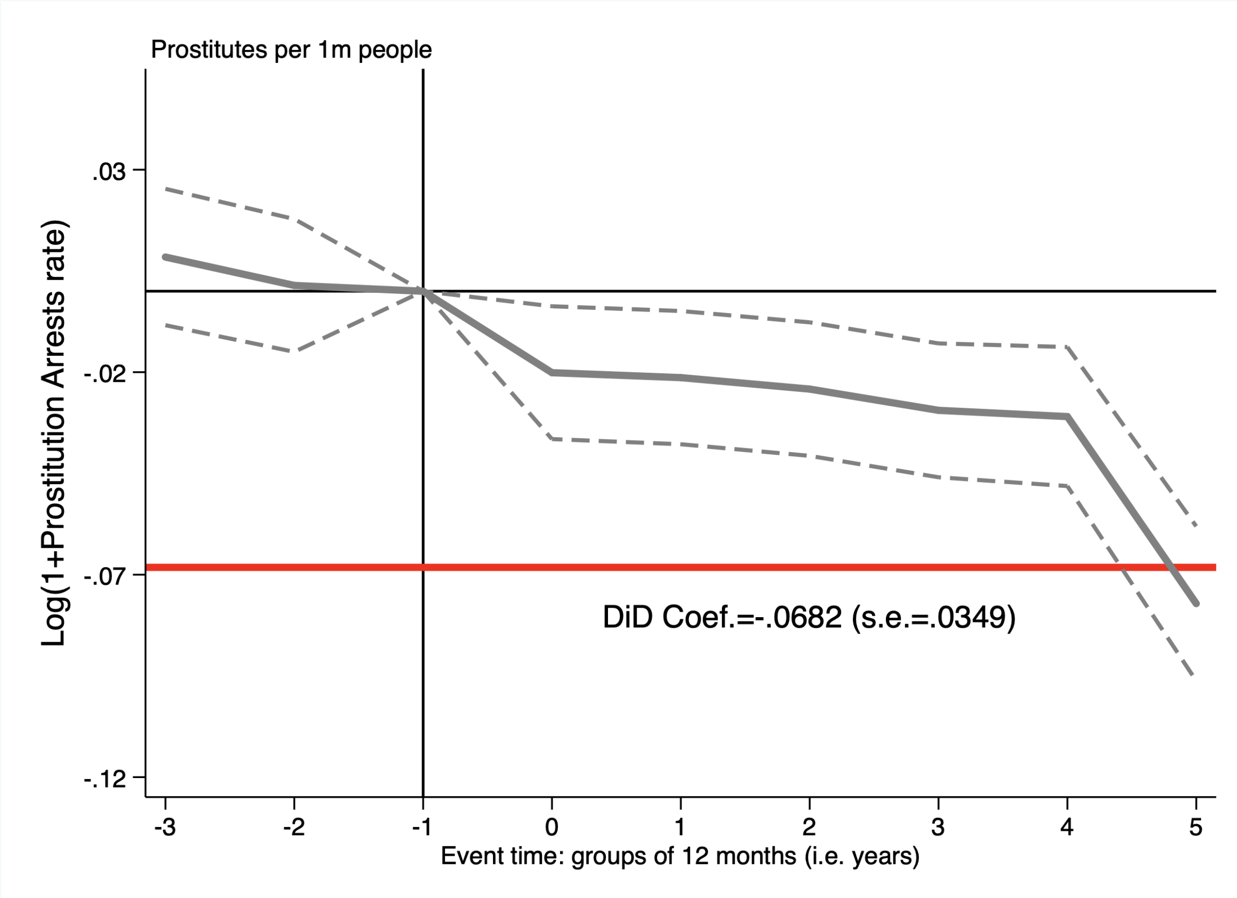
Notes: This figure plots the estimated coefficients of the event study analysis. On the horizontal axis, there is the event time in years (groups of 12 months). On the vertical axis, the coefficients are measured in terms of their effect on the dependent variable. The coefficients are measured relative to the omitted coefficient ($t = -1$). For each coefficient, the solid line graphs the point estimate, while dotted lines graph confidence intervals at the 90% level. The pattern of the estimated coefficients is consistent with the identification assumption: they show the absence of a pretrend and a trend break after the entry into force of unilateral divorce law. In fact, the two coefficients prior to the event (i.e., -3 and -2) are close to zero in the point estimate and statistically zero, respectively, whereas the coefficients after the event (i.e., 0, 1, 3, 4, 5) are statistically negative at standard significance levels. The solid red line is depicted at the height of the DiD coefficient. Moreover, this line displays the DiD coefficient and its standard error. The size of the coefficient of the last period is in line with DiD results.

Figure 2: Marriage and prostitution market equilibrium



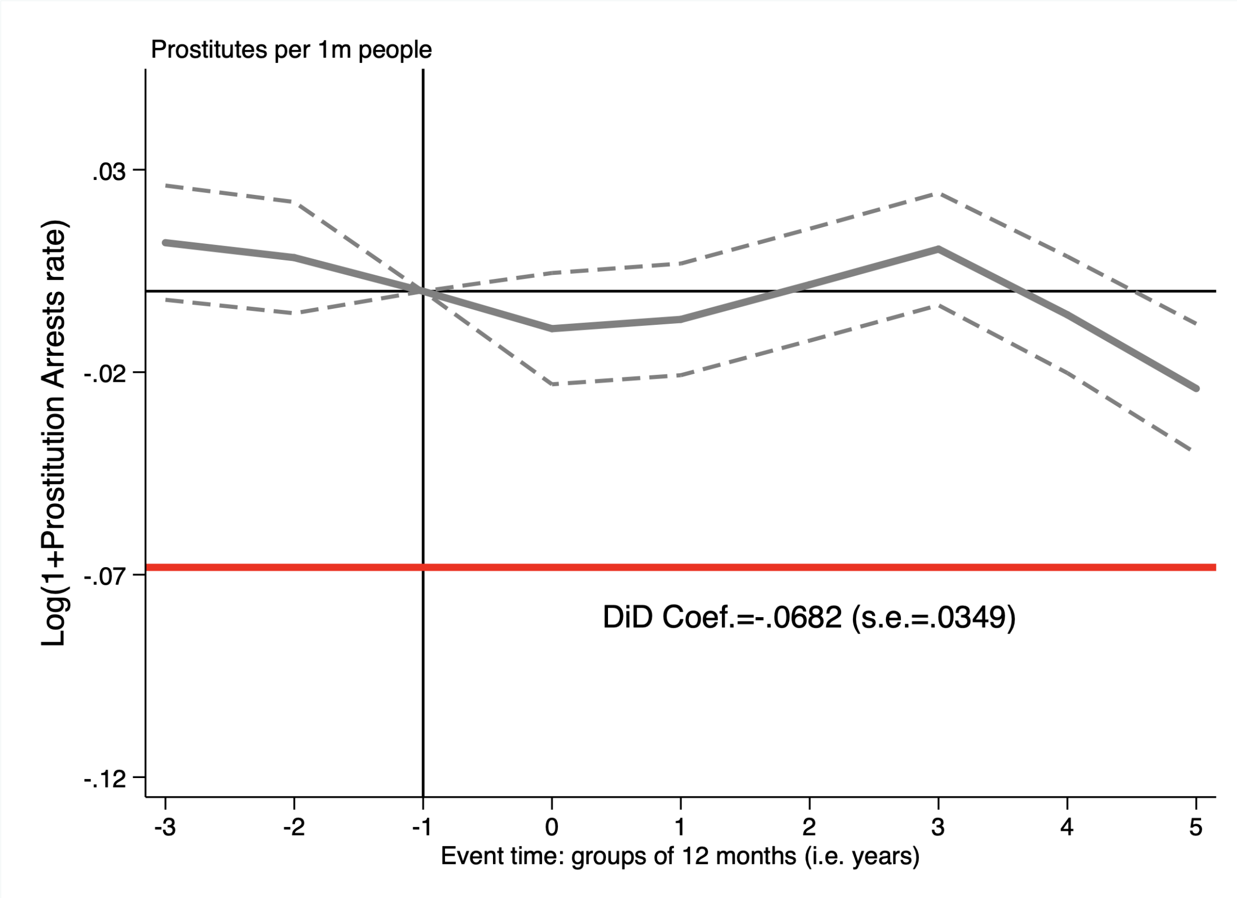
Source: Edlund and Korn (2002).

Figure 3: Event study: marrying-fertile age group



Notes: This figure plots the estimated coefficients of the event study analysis for arrested prostitutes in the marrying-fertile age group. The horizontal axis presents the event time in years (groups of 12 months). On the vertical axis, the coefficients are measured in terms of their effect on the dependent variable. The coefficients are measured relative to the omitted coefficient ($t = -1$). For each coefficient, the solid line graphs the point estimate, while dotted lines graph confidence intervals at the 90% level. The pattern of the estimated coefficients is consistent with the marriage compensation mechanism: they show the absence of a pre-trend and a trend break after the entry into force of unilateral divorce law. In fact, the two coefficients prior to the event (i.e., -3 and -2) are close to zero in the point estimate and statistically zero, respectively, whereas the coefficients after the event (i.e., 0, 1, 2, 3, 4, 5) are statistically negative at standard significance levels. The solid red line is depicted at the height of the DiD coefficient. Moreover, this line displays the DiD coefficient and its standard error. The size of the coefficient of the last period is in line with DiD results.

Figure 4: Event study: other ages



Notes: This figure plots the estimated coefficients of the event study analysis for arrested prostitutes of ages different from the marrying-fertile age group. The horizontal axis shows the event time in years (groups of 12 months). On the vertical axis, the coefficients are measured in terms of their effect on the dependent variable. The coefficients are measured relative to the omitted coefficient ($t = -1$). For each coefficient, the solid line graphs the point estimate, while dotted lines graph confidence intervals at the 90% level. The pattern of the estimated coefficients is consistent with the marriage compensation mechanism: the results are not driven by this age group.

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Online Appendix

A Background on the U.S. prostitution market

Prostitution is one of the most unsafe occupations in the U.S., worse than being an Alaskan fisherman, logger, or oil rig worker. As reported by HG.org (2017), the death rate for prostitutes in the U.S. is 204 out of every 100,000; that for Alaskan fishermen is 129 out of every 100,000. Moreover, statistics on prostitutes are conservative since prostitution is illegal in the U.S. (it is only allowed in Nevada in brothels and certain areas of the state). Prostitutes facing violence have nowhere to go without risking arrest themselves.

Dank et al. (2014) found that, in 2007, in eight major U.S. cities, prostitution generated a market value ranging from \$39.9 to \$290 million.[51] Furthermore, Pearl (1986) estimated that 16 U.S. cities spent on average \$15.3 million each year on prostitution control. More recently, Allard and Herbon (2003) found that prostitution arrests caused an expense of \$10.3 million in the city of Chicago alone. According to HG.org (2017), the annual average of approximately 70,000-80,000 arrests for prostitution costs American taxpayers \$200 million. Unsurprisingly, prostitution moves huge amounts of money in the form of both generated income and crime prevention.

The large amounts of money that prostitution moves around might originate from the lack of agreement on prostitution law. Opponents of prostitution contend that prostitution is dehumanizing (e.g., Farley et al. (2004); Farley (2003, 2004a); Farley and Butler (2012)). According to this line of thought, prostitutes are victims of physical and psychological violence. For example, Farley (2004b) estimated that approximately 85% to 95% of prostitutes wish to escape from prostitution but have no other options for survival. By contrast, those supporting legalization of prostitution argue that prostitutes chose to exchange their time and services for money as in any other job (e.g., TheEconomist (2004); Kempadoo (1999, 2007); Kempadoo et al. (2015)). Hence, it is the criminalization of prostitution that worsens prostitutes' standard of living. They claim that since prostitution cannot be stopped, legalizing it would be the only way to tax and "protect" prostitutes.

This ideological problem regarding how to regulate prostitution is all the more important because the U.S. prostitution market is highly stratified. Thus, the effects of any given regulation of the prostitution market might differ across market segments. The prostitution market in the U.S. can be divided into three segments. On the lowest tier, there are street prostitutes. Street prostitutes are usually controlled by pimps and thus make the

[51] The eight cities in the study were Denver, CO; Washington, DC; San Diego, CA; Miami, FL; Seattle, WA; Dallas, TX; Kansas City, MO; and Atlanta, GA.

least money. Further, they lack control over their choice of clients and are more likely to be victims of violence and to be arrested. Operating at the medium level are those working indoors in brothels, massage parlors, gentlemen's clubs and strip clubs. They usually enjoy better conditions than street prostitutes. Finally, escorts comprise the highest level of prostitutes. In this market segment, prostitutes have control over their choice of clients and "careers"; usually, they are not controlled by a pimp, earn high wages and are less likely to be victims of violence. This group is the one that best fits the image of prostitutes depicted by supporters of legalized prostitution. Prostitution in the medium and high tiers of this stratification takes place indoors: this is why it is also known as *indoor prostitution*, while street prostitution is also known as *outdoor prostitution*.[52]

This study makes use of data on female prostitution arrests, which are more likely to represent outdoor prostitution than indoor prostitution. However, I build a proxy variable for indoor prostitution when analyzing the mechanisms linking unilateral divorce and prostitution.

B Legislative background: The Divorce Revolution

Traditionally, in the U.S., divorce was permitted only on grounds of demonstrating guilt of misconduct by one of the two spouses and had to be agreed on mutually by both spouses (i.e., consent of the innocent party was required before a divorce was granted). Generally, such grounds were abandonment, cruelty, incurable mental illness, or adultery. The law was regarded as inadequate due to the major emotional and financial transaction costs involved in the verification of guilt of wrongdoing during the divorce process.

Thus, dissolution of marriages that were broken for mundane reasons (i.e., without misconduct by any spouse) was only possible if one of the two parties declared herself or himself guilty. In addition, since divorce had to be mutually agreed, the belief was that whenever husbands wished to divorce, they would bribe their wives to obtain their consent, while if wives wished to divorce, they could not afford to bribe their partners.

However, since divorce was considered to be against the public interest, civil courts formerly denied a divorce if there was evidence of cooperation between the two spouses or if they attempted to counterfeit the grounds for divorce. In fact, divorce could be barred even if one of the two spouses was found guilty. The three main reasons for refusing a divorce petition were as follows: recrimination, the suing spouse also being found guilty; condonation, forgiving the misconduct explicitly or implicitly by continuing to

[52] For further details on the stratification of the prostitution market in the U.S., see Shively et al. (2012).

live with the partner after knowing of it; and connivance, participating in the fault, such as organizing an act of adultery.

This law not only required marital wrongdoing to file the divorce petition but also punished spouses for such misbehavior. Indeed, both husband and wife could be punished if they were found guilty of wrongdoing. If the husband was at fault, he usually suffered the loss of child custody and the imposition of economic responsibilities; if the wife was found at fault, she might suffer the loss of alimony and child custody.

There was the tacit perception that the abolition of fault grounds and mutual consent would eliminate the hypocrisy that incited the use of perjury and the forgery of evidence to surmount strict legal hurdles (Marvell 1989; Rheinstein 1955, 1972; Mazur-Hart and Berman 1977). On the one hand, the guilt or innocence of the spouses would be irrelevant if no-fault divorce were available. On the other hand, consent of the partner would be useless if unilateral divorce were available.

In 1969, the California Family Law Act completely removed the requirements of fault as the basis for divorce and allowed spouses to file for divorce without the consent of their partner. This act established only two grounds for divorce: (i) irreconcilable differences; (ii) incurable insanity. Following Weitzman (1985), researchers have viewed this reform as the basis for both no-fault and unilateral divorce.

The focus of the reform was gender neutral: it assumed that the divorcee was economically independent and employable. Consequently, this law established two major bases for alimony awards: the divorcees' employability and the length of the marriage. If either of the divorcees were not economically independent, this law also helped her/him to garner new-skills or to improve existing skills to become self-sufficient.

The California Family Law Act started a movement to reform divorce laws in the U.S. known as "The Divorce Revolution", and various states followed suit. The movement gathered an apolitical consensus. Right-wingers viewed it as an expansion of personal rights and freedom. Left-wingers promoted it to prevent women from being locked into unfortunate marriages.

Unlike the case of California, "The Divorce Revolution" consisted of two steps: no-fault divorce and unilateral divorce. First, states moved to no-fault divorce regimes, which were already effective (to different degrees) in various states prior to 1950 while retaining mutual agreement. Next, states moved to unilateral divorce, requiring the consent of only one spouse to legally dissolve the marriage. This second step, which was uncommon before the 1960s, started in 1969 immediately after the passage of the California Family Law Act.

No-fault divorce does not change the bargaining structure within a marriage relationship. It solely reduces transaction costs by decreasing bargaining costs and eliminating financial penalties that could no longer be inflicted on at-fault spouses. Indeed, a no-fault divorce law eliminates the requirement of proof of guilt or innocence of either spouse. After the introduction of no-fault divorce, marriage dissolution could be lodged on grounds such as "incompatibility" or "irreconcilable differences". However, it has to be agreed to mutually by both partners. It was formulated simply to make marriage dissolution less dolorous and mournful.

Unilateral divorce goes a step further. It removes the property rights that mutual consent divorce grants either to the innocent spouse (for fault divorces) or to the spouse who does not wish to get divorced (for no-fault divorces). Namely, unilateral divorce could change spouses' behavior in two different ways. First, it allows spouses who are unable to prove the guilt of their partner or cannot afford to bribe their partner to file for divorce. Second, it changes the bargaining power between the members of the couple.

Furthermore, no-fault divorces are more complex to code since the definition of what constitutes a no-fault divorce is much broader than the definition of unilateral divorce. The literature classifies no-fault divorce into four categories: (a) living separate and apart as grounds for divorce; (b) incompatibility as grounds for divorce; (c) no-fault provisions added to traditional grounds as grounds for divorce; (d) no-fault is the sole grounds for divorce (Elrod and Spector 1997). These differences have given rise to widespread disagreement among scholars using no-fault divorce dates (Vlosky and Monroe 2002). An important point of divergence has been how to categorize fault-based laws that added "living separate and apart" provisions as no-fault laws. Even if such settlements consent to divorce without any proof of wrongdoing, the waiting period might be so long that it renders the provision either too weak to be regarded as no-fault or tantamount to a fault divorce law. The key difference is that true no-fault divorce laws are difficult to compare to legislative changes that simply revise fault-based grounds.

Unilateral divorce laws are easier to code; the only difference is whether the provision requires a separation period. The literature has treated as unilateral divorce regimes either both provisions with and without separation requirements or only provisions without separation requirements. Following Gruber (2004), I use unilateral divorce laws without separation for two reasons. First, since I code the law using a dummy variable, the comparison of identical unilateral divorce laws seems more reasonable and accurate. Second, even if unilateral divorce laws without separation requirements usually became effective later than those with separation requirements, I observe when such laws enter into effect since my sample period spans from 1980 to 2014.

Finally, coding might differ on whether enactment dates or effective dates were used.

The enactment date is the date on which a law is approved, while the effective date is the date on which a law enters into force. There can be a lag of months between the enactment and the effective date. Coding the effective date is usually more laborious than coding the enactment date since it necessitates a review of the session laws of each state. Nevertheless, I use the effective date since it is the one that is crucial in legal actions.

C Nature of the effect: Inflow vs Stock

Figure A.1 shows the effect of unilateral divorce on prostitution across age groups.[53]. As in the main regression, the dependent variable is in logs, each regression includes county, year and month fixed effects and county-year trends, and variance is clustered at the state level.

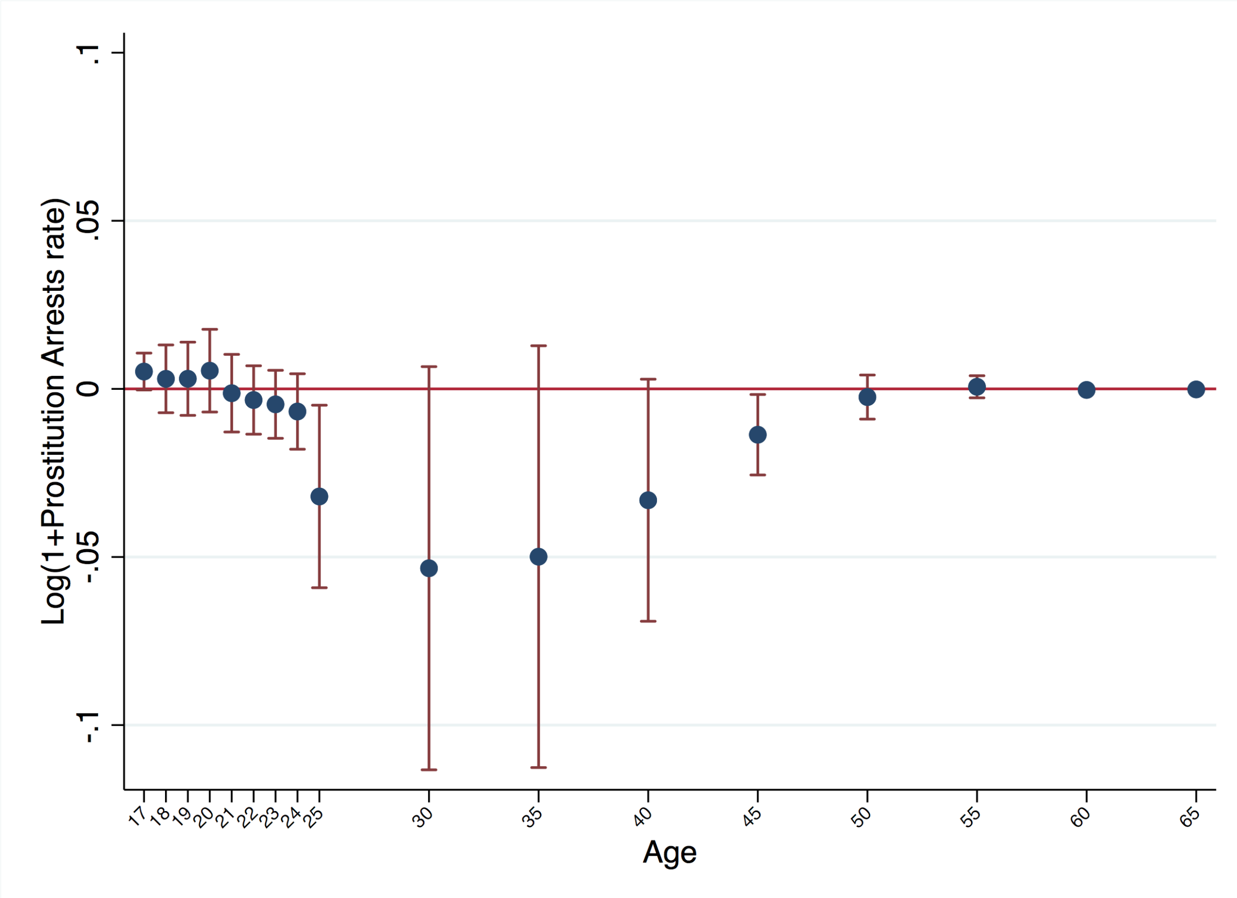
There are two ways in which unilateral divorce could affect prostitution: either by preventing women from becoming prostitutes (i.e., inflow effect) or by affecting prostitutes who are already in the market (i.e., stock effect). If unilateral divorce decreases young (old) prostitutes' arrests, it would support the former (latter) effect. Figure A.1 shows that unilateral divorce mainly reduces prostitution in women between 25 and 29 years old and in those between 45 and 49 years old.[54] Hence, there is evidence in favor of both effects.

In addition, Figure A.1 has two features worth mentioning. First, unilateral divorce does not affect prostitutes aged 17 and 24 years old and prostitutes aged 50 and 65 years old or older. In these two age groups, the point estimate is close to zero, and it is reassuring to find that the standard errors are narrow. Second, in contrast, in the age group of women age 25 and 49 years old, there seems to be a U-shaped curve, but standard errors are not as precise.

[53]Age groups are classified according to UCR database as in Table A.3. Starting at 25 years old, ages are grouped into five-year blocks: 25 to 29 years old, 30 to 34 years old, and so on and so forth.

[54]There could be the concern that there is no effect in the 17-24 age group since data are not pooled. However, Section G.1 presents the results of running a regression pooling together with arrests of female prostitutes between 17 and 24 years old and the results do not change.

Figure A.1: The effect of unilateral divorce on prostitution across age groups



Notes: This figure shows the effect of unilateral divorce on prostitution across age groups. Each coefficient and standard errors come from a regression, with the same structure as in the main specification, where the dependent variable was computed using the age group indicated. Confidence intervals are at the 90% level. These results suggest that unilateral divorce both prevents women from entering prostitution and affects women who are already prostitutes.

D List of crimes in UCR data set

Table A.1: List of offenses

Offense code	Offense
01A	Murder and non-negligent manslaughter
01B	Manslaughter by negligence
02	Forcible rape
03	Robbery
04	Aggravated assault
05	Burglary-breaking or entering
06	Larceny-theft (not motor vehicles
07	Motor vehicle theft
08	Other assaults
09	Arson
10	Forgery and counterfeiting
11	Fraud
12	Embezzlement
13	Stolen property-buy, receive, poss.
14	Vandalism
15	Weapons-carry, posses, etc.
16	Prostitution and commercialized vice
17	Sex offenses (not rape or prostitution)
18	Total drug abuse violations
180	Sale/manufacture (subtotal)
185	Possession (subtotal)
18A	Sale/mfg-Opium, coke, and their derivatives
18B	Sale/mfg-Marijuana
18C	Sale/mfg-Truly addicting synthetic narcotics
18D	Sale/mfg-Other dangerous non-narc drugs
18E	Possession-Opium, coke, and their derivatives
18F	Possession-Marijuana
18G	Possession-Truly addicting synthetic narcotics
18H	Possession-Other dangerous non-narc drugs
19	Gambling (total)
19A	Bookmaking (horse and sports)
19B	Number and lottery
19C	All other gambling
20	Offenses against family and children
21	Driving under the influence
22	Liquor laws
23	Drunkenness
24	Disorderly conduct
25	Vagrancy
26	All other non-traffic offenses
27	Suspicion
28	Curfew and loitering violations
29	Runaways

E Further information on the data set

E.1 Descriptive statistics

Table A.2 displays summary statistics for arrests of female prostitutes per 1,000,0000 inhabitants across treated and control states.[55] Data are at the county-month level, and treated states are disaggregated at pre- and post-treatment levels.

Table A.2: Summary statistics

	(1)	(2)	(3)	(4)	(5)
	Never-treated	Always-treated		Treated	
Arrests of female prostitutes per 1,000,000 inhabitants			pre	post	all
Mean	1.87	1.80	3.19	0.88	2.29
Std. dev.	13.83	20.44	16.27	6.39	13.38
Obs.	347,712	764,554	85,642	54,374	140,016
Max	2,042	3,969	1,058.22	484	1,058.22

Table A.3 shows summary statistics for arrests of female prostitutes per 1,000,0000 inhabitants broken out by age group. Columns (1) to (4) respectively report mean, standard deviation, minimum and maximum. Column (5) reports the share of each group, out of the total arrests of female prostitutes, without taking into account the population.[56]

[55] Arrests of female prostitutes per 1,000,000 inhabitants is computed as the number of arrested female prostitutes divided by population and multiplied by 1,000,000. Same computations are made for data on other crimes.

[56] Age groups are defined according to the UCR database.

Table A.3: Summary statistics

	(1)	(2)	(3)	(4)	(5)
Arrests of female prostitutes per 1,000,000 inhabitants	Mean	Std. dev.	Min	Max	Relative share (%)
Age group					
17	.0223	1.4267	0	1225.49	0.93
18	0.0586	0.9967	0	222	3.15
19	0.0809	1.3189	0	253.23	4.65
20	0 .0885	1.6375	0	461.04	5.07
21	0.099	2.1318	0	745.86	5.7
22	0.1017	2.2021	0	563.49	5.89
23	0.0998	2.0089	0	485.63	5.69
24	0.0979	1.7881	0	370.88	5.37
25-29	0.4155	4.7445	0	889.3	22.85
30-34	0.3216	3.8326	0	2849	17.08
35-39	0.2219	2.1452	0	411.07	11.64
40-44	0.1327	1.4215	0	309.26	6.9
45-49	0.0681	1.1198	0	545.55	3.35
50-54	0.0243	0.5573	0	212.95	1.2
55-59	0.0084	0.4604	0	236.91	0.37
60-64	0.0029	0.2399	0	122.44	0.13
65 or older	0.0022	0.2487	0	134.12	0.07
Total	1.87	18.11	0	3969.04	100

Figure A.2 displays arrests of female prostitutes per 1,000,0000 inhabitants (in the same logarithmic transformation as the dependent variable) for the three groups of states: treated, never treated and already treated. Vertical lines represent the year in which unilateral divorce laws became effective in each of the treated states.

This figure cannot be used to assess whether the trends of treated and control groups are parallel since the effective dates of unilateral divorce laws differ across states. However, it shows that, as many more states adopt unilateral divorce, treated states experience a substantial decline in arrests of female prostitutes per 1,000,0000 inhabitants, in line with my findings. In other words, as treated states adopt unilateral divorce, arrests of female prostitutes decrease more severely there than in control states.

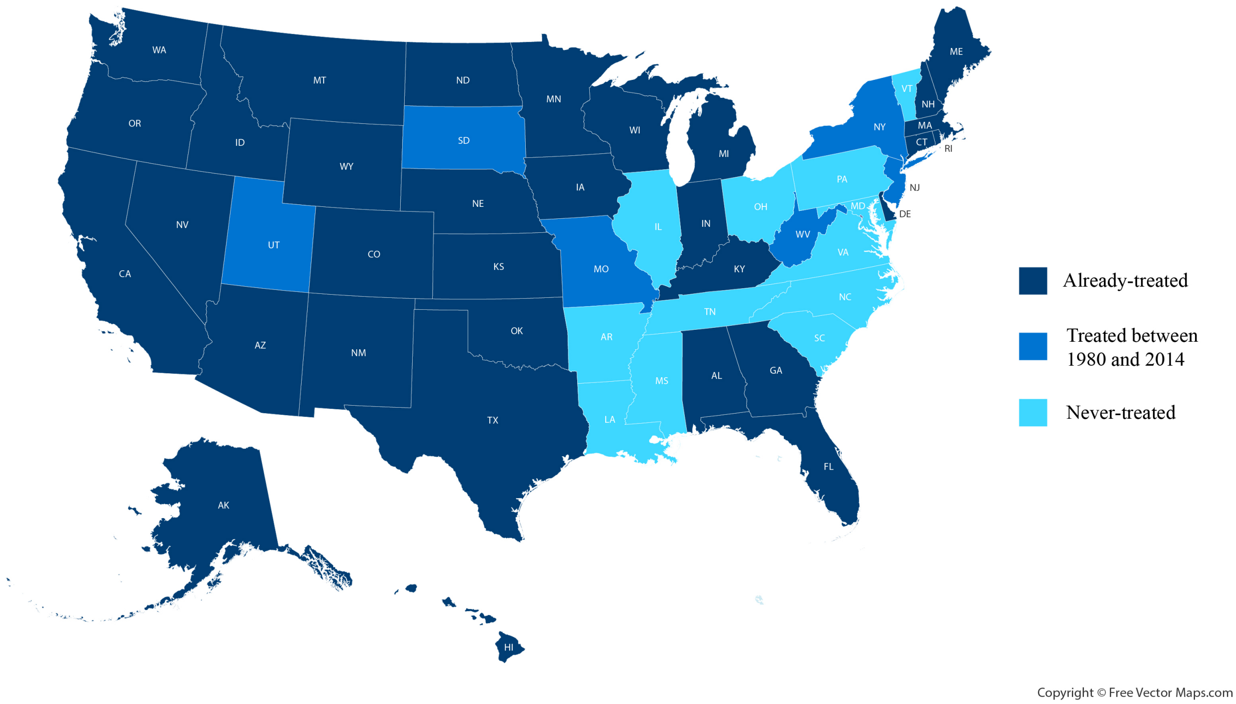
Figure A.2: Evolution of female prostitutes arrests in treated and control states

Notes: This figure plots arrests of female prostitutes per 1,000,0000 inhabitants, in the same logarithmic transformation as the dependent variable, for the three groups of states analyzed in the study: treated, never treated and already treated. Vertical lines represents the year in which unilateral divorce law became effective in each of the treated states.

F Effective date of unilateral divorce laws across U.S. states

The effective date is established using Thomson Reuters Westlaw. In the section "Statutes and Court rules", Thomson Reuters Westlaw keeps track of different legislations and when they became effective. This procedure establishes an effective month for each state that experienced a change in divorce law during my sample period. Figure A.3 maps treated and control states (i.e., never treated and already treated, respectively).

Figure A.3: Treated and control states



Notes: This figure maps U.S. states according to their treatment status.

G Comment on potential mechanisms: marriage compensation mechanism

G.1 Comparison group

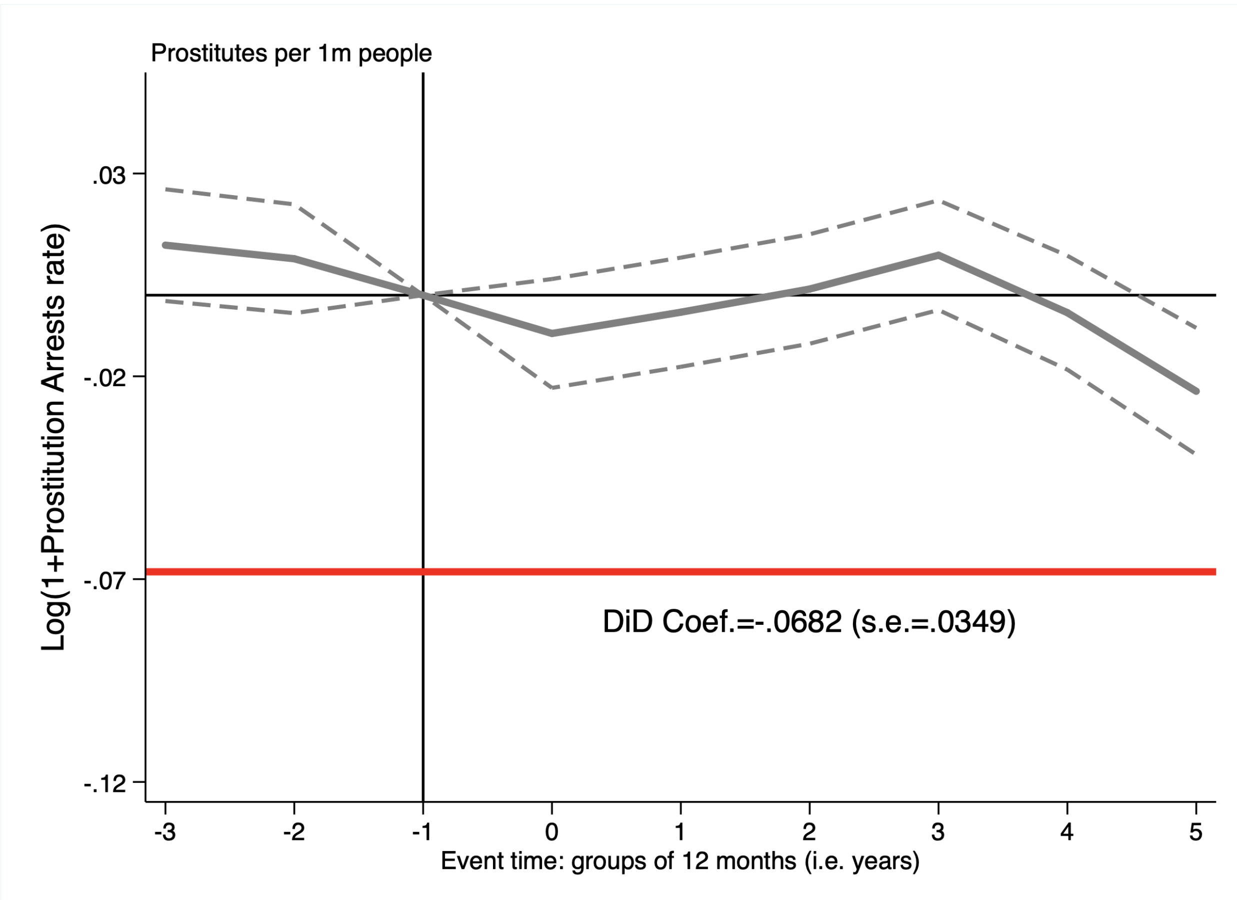
There could be the concern that the finding that unilateral divorce has a greater impact on arrested prostitutes of marrying-fertile age is due to the choice of using arrested prostitutes of other ages as the comparison group. This latter group is composed of arrested prostitutes either between 17 and 24 years old or strictly older than 49 years old since the marrying-fertile age group is formed by prostitutes between 25 and 49 years old. The potential concern is that results are driven by the inclusion of prostitutes strictly older than 49 years old that might seem less frequent than their younger counterparts.

To address this issue, this section presents the results of running equation (6) but using arrested prostitutes between 17 and 24 years old only (i.e., arrested prostitutes older than 49 years old are excluded). Using only prostitutes between 17 and 24 years old signifies using only prostitutes of fertile age but too young to get married.

Table A.4 shows the results of running the same analysis as before but for this age group. Findings are qualitatively similar: there is evidence that unilateral divorce law has a larger impact on arrested prostitutes of marrying-fertile age than on arrested prostitutes of other ages. This evidence supports the marriage compensation mechanism.

Figure A.4 shows the results of running equation (2) for the "17-24 years old" sample. In line with the marriage compensation mechanism, the coefficients show that the results are not driven by this age group.

Figure A.4: Event study: "17-24 years old" sample



Notes: This figure plots the estimated coefficients of the event study analysis for arrested prostitutes in the "17-24 years old" sample. On the horizontal axis is the event time in years (groups of 12 months). On the vertical axis, the coefficients are measured in terms of their effect on the dependent variable. The coefficients are measured relative to the omitted coefficient ($t = -1$). For each coefficient, the solid line graphs the point estimate, while dotted lines graph confidence intervals at the 90% level. The pattern of the estimated coefficients is consistent with the marriage compensation mechanism: results are not driven by this age group.

Table A.4: Potential mechanisms: marriage compensation

VARIABLES	(1) Log(1+y) Marrying-Fertile age	(2) IHS Marrying-Fertile age	(3) Log(1+y) 17-24 y.o.	(4) IHS 17-24 y.o.	(5) Log(1+y) Joint regression	(6) IHS Joint regression
Unilateral	-0.0800	-0.0945	-0.0176	-0.0230	-0.0282	-0.0345
	(0.0521)	(0.0615)	(0.0155)	(0.0186)	(0.0232)	(0.0279)
Dummy Marrying -Fertile age					0.0774***	0.0929***
					(0.0163)	(0.0197)
Unilateral*Dummy Marrying-Fertile age					-0.0352**	-0.0422**
					(0.0172)	(0.0208)
Observations	1,252,282	1,252,282	1,252,282	1,252,282	2,504,564	2,504,564
Clustered variance at State level	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓
County Year Trends	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓

Clustered standard errors at state level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table displays the estimated coefficients of running specification (4) for marrying-fertile age sample and for the "17-24 years old" sample. Data are at the county-month level. Standard errors are clustered at state level. Each column of the table uses a different dependent variable. Column (1) uses $\log(1+y)$ of the marrying-fertile age group, column (2) uses the IHS transformation of the marrying-fertile age group, column (3) uses $\log(1+y)$ of the "17-24 years old" group, and column (4) uses the IHS transformation of the "17-24 years old" group. Columns (5) and (6) show the results of running equation (6).

G.2 Indoor Prostitution

A potential concern could be that female prostitutes of marrying and fertile age became more difficult to arrest for reasons disconnected to their opportunity cost of getting married. As far as I can determine, there is no clear plausible mechanism that could support this explanation.[57]

CPS data provide information on the occupational code; this allows me to restrict the sample to potential indoor prostitutes. Using the occupational code, I can restrict the sample to female respondents working in industrial sectors connected to indoor prostitution. Hence, I obtain a reasonable proxy for potential indoor prostitutes.[58]

Namely, I consider the following regression model similar to regression model (4):

$$log(1 + Indoor\ Prostitution_{smy}) = \beta Unilateral_{smy} + \alpha_m + \alpha_y + \alpha_s + \alpha_s * y + \varepsilon_{smy} \quad \text{(A.1)}$$

where $Indoor\,prostitutes_{smy}$ is the number of women in occupational sectors that contain indoor prostitution businesses per 1,000,000 inhabitants in state s, month m and year y; α_m, α_y and α_s are respectively month, year and state fixed effects; and $\alpha_s * y$ are state-year linear trends. As in the previous analysis, I split the sample depending on the age of female respondents. In particular, I split the sample into two groups: indoor prostitutes of marrying-fertile age and indoor prostitutes of other ages.

Columns (1) and (4) of Table A.5 show the results of running equation (8) for marrying-fertile age and other ages. The results show that unilateral divorce decreases potential indoor prostitutes of marrying-fertile age but does not affect potential indoor prostitutes of other ages. Columns (2) and (5) report results using IHS, while columns (3) and (6) reports the results in levels. The results are stable across functional forms.

[57] Cunningham and Kendall (2011a) hypothesized that "the Internet and other modern technologies are drawing prime-aged (street) prostitutes into indoor work". There could be the concern that this hypothesis is driving my findings. For this to occur, internet would need to be introduced simultaneously to unilateral divorce laws. Using data on indoor prostitutes would shed light on this mechanism too.

[58] Appendix Section H provides the exact list of the occupational codes used.

Table A.5: Potential mechanisms: marriage compensation, CPS data

	(1)	(2)	(3)	(4)	(5)	(6)
	Log(1+y)	IHS	Levels	Log(1+y)	IHS	Levels
VARIABLES	Marrying-fertile age	Marrying-fertile age	Marrying-fertile age	Other ages	Other ages	Other ages
Unilateral	-0.317**	-0.358**	-13.01*	0.105	0.115	9.480
	(0.141)	(0.159)	(7.342)	(0.117)	(0.131)	(8.799)
Observations	20,400	20,400	20,400	20,400	20,400	20,400
Clustered variance at State level	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓
State Year Trends	✓	✓	✓	✓	✓	✓

Clustered standard errors at state level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table displays the estimated coefficients of running specification (A.1). Data are at the state-month level. Standard errors are clustered at the state level. Each column of the table uses a different dependent variable. Columns (1), (2) and (3) respectively use number of potential indoor prostitutes of marrying-fertile age in logs, IHS and levels. Columns (4), (5) and (6) use the same variable but for potential indoor prostitutes of other ages. Each column includes state fixed effects, state-year trends, year fixed effects and month fixed effects.

H Industry sectors used to measure indoor prostitution

To measure potential indoor prostitutes, I restrict CPS data to the following occupational codes in the table below. The names of the variables are drawn from the monthly extracts of the CPS Uniform database of the Centre of Economic Policy Research (CEPR).[59] In order to code such variables, it is useful to use both SIC and NAICS systems.

Specifically, I restrict my sample to women working in industry sectors composed of strip clubs and escort-girl services (i.e., sectors that comprise indoor prostitution establishments). Note that these industry sectors are composed of various occupations, among which there are strip clubs, massage parlors and escort-girls services. Hence, women in this sample might be working in other occupations too. However, this sample is more likely to be formed by prostitutes. Recall that in the U.S., the prostitution market is highly stratified. Women arrested for prostitution are very likely street prostitutes, who make up the low segment of the market. The sample I extract from CPS data is composed of strip clubs, massage parlors and escort-girls services, who form the medium and high segments of the market. According to the theory, indoor prostitutes are as likely to respond to an increase in p_m as outdoor prostitutes.

Table A.6: Occupational codes used

Occupational code	Strip-clubs	Escort services
ind70	798	809
ind80	791	810
ind03, ind09, ind12, ind14	8590	9090
occ70	933	
occ80	469	
occ03, occ11, occ12	4520, 4650	

For variables ind70 and ind80, strip clubs belong to an occupational sector named "Miscellaneous entertainment and recreative services", while escort services belong to "Miscellaneous personal services". In the last three variables, these names respectively change to "Other amusement, gambling, and recreative services" and "Other personal services". [60] This sample spans from 1980 to 2014. Sectors for variables occ70 and occ80

[59] http://ceprdata.org/cps-uniform-data-extracts/

[60] An example of the SIC code classification is `https://www.osha.gov/pls/imis/sic_manual.display?id=267&tab=description`

are labeled as "Personal service occupations, not elsewhere classified". Finally, Sectors for variables occ03, occ11 and occ12 are labeled as "Miscellaneous personal appearance workers" and "Personal care and service workers, all other".

I Comment on potential mechanisms: fight against crime mechanism

I.1 Officers

There could be the concern that hired officers do not vary considerably over years and that this lack of variation is driving the results of the police mechanism.

To address this issue, this section considers equation (2) but makes use of two different transformations of the dependent variable. First, I use the first difference of officers per 1,000 inhabitants. In other words, I use the variation (i.e., increase/decrease) of hired officers normalized by a state's population. Second, I use the growth rate of officers per 1,000 inhabitants. Results are presented in the same fashion as in the police mechanism analysis.

I find no empirical evidence supporting that unilateral divorce correlates with a reduction of officers.

Table A.7: Potential mechanisms: fight against crime mechanism

VARIABLES	(1) First Difference Officers	(2) First Difference Officers	(3) First Difference Officers	(4) First Difference Officers	(5) Growth rate Officers	(6) Growth rate Officers	(7) Growth rate Officers	(8) Growth rate Officers
Unilateral	0.00535	-0.00554	-0.00758	-0.0166	-0.000861	-0.00181	-0.00607	-0.00792
	(0.00665)	(0.00753)	(0.00916)	(0.0160)	(0.00418)	(0.00437)	(0.00439)	(0.00748)
Observations	2,150	2,150	1,750	1,750	2,150	2,150	1,750	1,750
Clustered variance at State level	✓	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
State Year Trends		✓		✓		✓		✓
Sample	1971-2016	1971-2016	1980-2014	1980-2014	1971-2016	1971-2016	1980-2014	1980-2014

Clustered standard errors at state level in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: This table displays the estimated coefficients of running specification (5) for two different transformations of the dependent variable. Data are at the state-year level. Standard errors are clustered at state level. Columns (1) to (4) use the dependent variable in levels; columns (5) to (8) use the dependent variable in logs.

I.2 Other crimes

This section presents results of running my main specification using as dependent variable each of the main categories of offenses recorded by UCR (28 main categories of offenses excluding prostitution).[61] Such offenses are recorded in two panels depending on whether there is evidence in the literature that they are connected to prostitution. Namely, Panel A shows offenses not connected to prostitution, while Panel B displays offenses connected to prostitution.

There is evidence in the literature (Urban Justice Center 2005; Dank et al. 2014; Cunningham et al. 2017; HG.org 2017) that prostitution is connected to different crimes. Using such literature, I divided offenses in two groups: connected and not connected to prostitution, as shown in Table A.8.[62]

Each cell in the column shows the estimated coefficient, and its standard error, associated with unilateral divorce using the corresponding offense in the row as the dependent variable transformed according to the corresponding column. In fact, each column shows the results of running the abovementioned regression with a different functional form of the dependent variable. Columns (1), (2) and (3) respectively use the dependent variable in logs, IHS and levels. Each regression includes month and year fixed effects, county fixed effects and linear trends, and variance is clustered at the state level.

[61] All the categories are reported in Appendix Section D

[62] Two crimes in Panel A could have been in Panel B. First, for "total drug abuse" (i.e., drugs crimes/use), there is evidence in the literature that both prostitutes and prostitutes' clients make use of drugs. However, their relative percentage with respect to the whole "drugs market" is unclear. This is why such regressions' results also appear in Section 7. Second, "vagrancy" there is evidence in the literature that prostitutes' arrests are seldom reported as "loitering" (for example, the New York State Division of Criminal Justice Services classifies "loitering" as including "loitering for prostitution"). Given the close connection between "vagrancy" and "loitering", the former could also be considered as an offense connected to prostitution.

Table A.8: Potential mechanisms: fight against crime mechanism

DEPENDENT VARIABLE	(1) Log(1+y)	(2) IHS	(3) Levels
Panel A: Crimes not connected to prostitution			
Robbery	-0.001721	-0.00221	-0.00031
	(0.00836)	(0.0102)	(0.08983)
Burglary	0.08697**	0.10148**	1.81443***
	(0.03777)	(0.04509)	(0.58084)
Larceny	0.03422	0.02712	9.46527*
	(0.08818)	(0.09835)	(4.78697)
Motor Theft	0.02040	0.02336	-0.60396
	(0.02898)	(0.034473)	(1.49761)
Other Assault	-0.04920	-0.05902	0.98405
	(0.09551)	(0.10851)	(4.30007)
Arson	0.00079	0.00079	0.03033
	(0.00734)	(0.00891)	(0.09112)
Forgery	-0.04906	-0.06002	0.39481
	(0.05031)	(0.05987)	(0.64869)
Fraud	-0.24433	-0.27693	-1.49883
	(0.14994)	(0.16957)	(6.56632)
Embezzlement	0.00188	0.00162	0.09943
	(0.03516)	(0.04353)	(0.22858)
Stolen Property	-0.00154	-0.00236	-0.21224
	(0.01479)	(0.01728)	(0.36632)
Vandalism	0.0256	0.0277	1.13909
	(0.0589)	(0.0681)	(1.13533)
Total Drug abuse	-0.0655	-0.0809	-1.02097
	(0.0906)	(0.102)	(6.01042)
Gambling	0.00523	0.00664	-0.05416
	(0.01352)	(0.01642)	(0.15739)
Offences against family and children	-0.27179	-0.32726	-1.91609
	(0.1766)	(0.21361)	(1.65182)
Driving under alcohol influence	-0.33186	-0.38589	-7.97683
	(0.23374)	(0.26046)	(10.0430)
Liquor laws	-0.06766	-0.09378	9.06771
	(0.12086)	(0 .14263)	(10.6131)
Drunkeness	-0.02130	-0.02631	-2.41075
	(0.07916)	(0.09107)	(3.63117)
Disorder Conduct	-0.01541	-0.01903	0.04367
	(0.06861)	(0.07877)	(2.56150)
Vagrancy	-0.04257**	-0.05104**	-0.59007*
	(0.01704)	(0.02017)	(0.33096)
Other Non Traffic Offences	-0.09939	-0.10798	-10.1071
	(0.1476)	(0.16343)	(17.5948)
Suspicion	0.00266	0.00378	-0.03259
	(0.00336)	(0.00387)	(0.15955)
Runaways	-0.14292	-0.16488	-2.64762
	(0.09808)	(0.11373)	(2.17062)
Panel B: Crimes connected to prostitution			
Homicide	-0.00891	-0.01068	-0.16131*
	(0.00541)	(0.00647)	(0.08153)
Rape	-0.00333	-0.00412	0.01808
	(0.00453)	(0.00563)	(0.03788)
Assault	-0.09301*	-0.10923*	-1.24446
	(0.05274)	(0.06289)	(0.81679)
Weapon	-0.02623*	-0.03184*	-0.11522
	(0.01409)	(0.01687)	(0.14296)
Sex Offences	-0.02103	-0.02563	0.0069
	(0.03223)	(0.03965)	(0.27205)
Curfew and Loitering violations	-0.00365	-0.00546	-0.08268
	(0.04229)	(0.04943)	(0.95489)
Observations	1,252,282	1,252,282	1,252,282

Clustered standard errors at state level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table displays the estimated coefficients of running specification (1) for each each offense recorded by UCR (row) and functional form of the dependent variable (column).

J Comment on demand mechanisms

The demand function considered in Section 7 is a simplified version of the original one discussed in Edlund and Korn (2002). In fact, in Edlund and Korn (2002), the demand for prostitution is a weighted average of the demand for prostitution by unmarried men and of the demand for prostitution by married men. Both demands are an increasing function of men's earnings. In addition, the demand of prostitution by married men is also a decreasing function of p_m.

As for the former, I run a regression using CPS data, where the dependent variable is the average wage of men. The specification has the same structure as the specification shown in equation (3). Table A.9 shows the results of running this equation for men's real wages in logs (column (1)) and in levels (column (2)), respectively. All in all, I do not find suggestive evidence that unilateral divorce law decreases men's earnings and, as a consequence, the demand for prostitution. Indeed, the lower bounds of the 90% confidence intervals associated with estimated coefficients of columns (1) and (2) suggest that the reduction in men's real wages is at most between 3.6% and 3.9%.[63]

As for the latter, it implies that an increase in p_m could decrease the demand for prostitution by married men as well as reduce the supply of prostitution. To study this channel, I would need data on the demand for prostitution by married men, which I do not have. Hence, it is important to note that finding that unilateral divorce reduces the demand for prostitution by married men would not be inconsistent with the marriage compensation channel.

[63]Each estimate corresponds to the lower bound of a confidence interval. The sample mean of the dependent variable used in column (2) (i.e., average men's real wage) is 13.2.

Table A.9: Potential mechanisms: men's wage

VARIABLES	(1) Log Average Men's Real Wage	(2) Average Men's Real Wage
Unilateral	-0.0127	-0.257
	(0.0145)	(0.161)
Observations	20,400	20,400
Clustered variance at State level	✓	✓
State FE	✓	✓
Year FE	✓	✓
Month FE	✓	✓
State Year Trends	✓	✓

Clustered standard errors at state level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table displays the estimated coefficients of running the specification (3) for men. Data are at the state-month level. Standard errors are clustered at state level. Each column of the table uses a different dependent variable. Column (1) uses average men's real wage in logs; column (2) uses average men's real wage in levels. Each column includes state fixed effects, state-year trends, year fixed effects and month fixed effects.