The Spillover Effects of E-Verify on High-Skilled Citizen Women*

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Abstract

Verify Employment Eligibility (E-Verify) is designed to curb the hiring of unauthorized immigrants. This paper is the first to examine the spillover impact of E-Verify on highly-educated citizen women's labor supply (particularly those with young children). Using variation in implementation of E-Verify across states and a state-level panel data set, I find that E-Verify reduces the labor supply of high-skilled citizen women by 0.5 to 1.2 percent. These estimates are larger for women with children. I argue that this reduction is due to an increase in costs of household services where undocumented immigrants are over-represented. The magnitudes of my estimates suggest that E-Verify generated $6.1 billion in social costs of lower labor supply of high-skilled citizen women.

Keywords: immigration, substitute, domestic work, household service.

JEL Classification: J15, J16, J22, J24, J61, Z18

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1 Introduction

Verify Employment Eligibility (E-Verify) is a free federal identity and work authorization verification system that aims at reducing the hiring of undocumented immigrants. Specifically, E-Verify requires employers to check the employee's eligibility to work legally. E-Verify queries as a share of new hires has grown quickly in the past decade. For example, in 2007 E-Verify covered only three percent of new hires, whereas by 2018, E-Verify queries as a share of new hires is roughly 35 percent (Figure 1).[1] An extensive literature has studied the impact of E-Verify on the migration flow, labor supply, and earning of undocumented immigrants (Amuedo-Dorantes and Bansak, 2012, 2014; Bohn and Lofstrom, 2012; Amuedo-Dorantes et al., 2015; Chassambouli and Peri, 2015; Orrenius and Zavodny, 2015, 2016; Orrenius et al., 2018).[2] However, evidence about the spillover effects of E-Verify on labor outcomes of natives is somewhat limited.[3]

The goal of my paper is to study the spillover impact of E-Verify on the labor market outcomes of high-skilled citizen women (who have completed college or more). I focus on high-skilled female workers since it is well-documented that high-skilled women's labor supply has a positive relationship with the number of undocumented immigrants (Furtado and Hock, 2010; Barone and Mocetti, 2011; Cortes and Tessada, 2011; Farre et al., 2011; Cortes and Pan, 2013; Amuedo-Dorantes and Sevilla, 2014; Peri et al., 2015; East and Velasquez, 2019). One way undocumented immigrants could affect the labor supply of high-skilled women citizens is through changes in the cost of household services since undocumented immigrants

[1]Figure 1 shows the information about E-Verify use rate for the period 2005-2018. Data are from U.S. Citizenship and Immigration Services (USCIS), Small Business Administration, Census Bureau, Westat, and Cato Institute.

[2]In general, previous studies found that E-Verify had a negative impact on the hourly wage and employment rates of likely undocumented immigrants.

[3]Previous findings on the E-Verify's effect on citizen workers labor outcomes have mostly focused on low-skilled citizen workers who are likely to compete with undocumented immigrants in the labor market (see Amuedo-Dorantes and Bansak, 2014; Bohn et al., 2015). These are substitutes at work (low-skilled for low-skilled) while no one has looked at substitutes at home (low-skilled for high-skilled). This paper attempts to fill this gap in the literature.

are over-represented in household services as maids, housekeeping cleaners, gardeners, and workers in dry cleaning and laundry services (Passel and Cohn, 2016).

My empirical strategy is to exploit the cross-state variation in the implementation of E-Verify. To illuminate the potential unintended consequences of E-Verify on citizen female labor supply, I collect the data on the adoption of E-Verify at the state level and merged these data to a 2005-2017 state panel on labor supply. This allows me to estimate a difference-in-differences model with state and year fixed effects. There are two main concerns with my identification strategy. First, the labor supply difference, between states that adopted E-Verify compared with those that did not, varies over time. Second, E-Verify implementations are endogenous.

I do a number of things to address the common trends concern. First, I conduct an event study to see if there is a systematic difference in high-skilled citizen women labor supply before the E-Verify implementation across states. The event study results show that labor supply of high-skilled citizen women are indistinguishable from zero in pre-trend period across states, but then demonstrate a level shift after E-Verify implementation, with high-skilled women in implemented states decrease their labor supply over time.

Second, as a test for endogenous policy implementation, I attempt to predict the implementation of E-Verify using low-skilled immigrant share of labor force/total population. Significant coefficients on the low-skilled immigrant share of labor force/total population would indicate that the policies were implemented in response to pre-existing trends in the share of low-skilled immigrants, and this would limit the causal interpretation of my results. I find that the coefficients on the share of low-skilled immigrants are generally insignificant. This serves as strong evidence that E-Verifies were not endogenously implemented in response to particularly high low-skilled immigrant share, and this supports the causal interpretation of my labor supply results.

My main findings show that implementation of E-Verify decreases labor supply of high-skilled citizen female workers. The impact is stronger for mothers, specifically, I estimate that adopting E-Verify is associated with a one percent decrease in labor force participation rate and a 25 minute decrease in hours worked per week by mothers. Turning to high-skilled men and fathers as a placebo group, I do not find any similar effects on the labor supply or time spent on household activities. These results are consistent with a more elastic of women's labor supply (Caldwell and Oehlsen, 2019).

I next study possible channels in which E-Verify affects high-skilled women workers. A number of findings suggest that a change in the price of household services is a crucial channel. First, looking directly at the undocumented immigrants, I replicate the findings of Amuedo-Dorantes and Bansak (2014), extending the analysis by including 2013, 2014, 2015, 2016 and 2017. I confirm that E-Verify substantially decreases the labor supply of undocumented immigrants. Second, I find that E-Verify is associated with an increase in the cost of household services, proxied by the wage of household workers. Third, using the American Time Use Survey (ATUS) and Consumer Expenditure Survey (CEX), I find that E-Verify increases the time spent on household activities among mothers and decreases household services purchased on the market of female headed households.

My paper makes several contributions to the literature. First, to my knowledge, no previous literature has looked at the spillover effects of E-Verify on high-skilled women labor outcomes. Over the past two decades, one of the central components of comprehensive immigration reform proposals is how to regulate more than 11 million undocumented immigrants currently in the U.S..[4] Understanding the spillover effects of E-Verify is crucial to the evaluation of future regularization proposals. Second, I provide evidence on a possible mechanism in which E-Verify affects high-skilled women's labor supply: higher cost of household services.

My work is closest to works of Cortes and Tessada (2011) and East and Velasquez (2019).

[4]The estimation of the number of undocumnted immigrants in the U.S. is from Krogstad et al. (2019).

While both use a sample similar to mine, they look at different research questions. Cortes and Tessada (2011) examines the impact of the number of immigrants on high-skilled women's labor supply, using immigrant enclaves as an instrument for migration . East and Velasquez (2019) examines the impact of Secure Communities (and not E-Verify) on the labor supply of high-skilled women using a difference-in-differences (DD) framework.

The main difference between this paper and East and Velasquez (2019) is the immigration policy studied. Specifically, East and Velasquez (2019) studies the impacts of Secure Communities (SC) and this paper studies the impacts of E-Verify. While both SC and E-Verify are designed to regulate undocumented immigrants, the main difference between these policies is SC deports undocumented immigrants while E-Verify does not. In other words, SC is a much tougher policy than E-Verify. Thus, one would expect SC to have a negative impact on the labor supply of household services, but not necessarily E-Verify. In fact this paper finds that the less-extreme policy of checking on the immigration status prior to employment has a similar negative externality on citizen female labor supply. This paper is the first to examine the spillover impact of E-Verify on highly-educated citizen womens labor supply. Furthermore, East and Velasquez (2019) relies on a continuous DD coefficient between 0 and 1 while mine is a binary variable.

This paper also relates to a large literature on understanding impact of immigration on natives' outcomes. I focus in particular on the labor supply of high-skilled women. The large literature looks at other outcomes, including (among others) population growth, education, internal migration, wages, patents, crime, and innovation (Card, 2007; Kerr, 2007; Hunt and Gauthier-Loiselle, 2010; Ottaviano and Peri, 2012; Chassambouli and Peri, 2015; Freedman et al., 2018).

The rest of the paper proceeds as follows. Section 2 discusses the data, followed by the empirical framework in Section 3. The results are presented in Section 4. Section 5 concludes.

2 Data

In this section, I describe information about the implementation of E-Verify as well as the data I use to measure labor market outcomes, time use, and household production consumption.

E-Verify Data.— I gather information about enactment and implementation dates of E-Verify mandates at the state-level from the National Conference of State Legislatures[5], as well as Amuedo-Dorantes et al. (2015), and various news articles. Figure 2 shows the rollout of the E-Verify across states in the U.S.. As observed, there is crucial variation in the adoption of E-Verify, both across states and through time, which I will exploit in identifying the effect of E-Verify.

Labor Market Outcomes Data.— To measure the labor market effects of E-Verify, I use the local-level data drawn from the 2005-2017 American Community Survey (ACS) Integrated Public Use Microdata Series data (Ruggles et al., 2019).[6] The ACS is a repeated cross-sectional dataset with a large sample size covering a one percent random sample of the U.S.. I restrict the sample to people aged 20-64 who report being in the labor force and not enrolled in school.[7] To create a state panel, I collapse the ACS data to the state by year level, using the sample weights. The results are robust to the use of individual-level data (Table A.13 and Table A.15).

My main outcome variables are the labor supply of high-skilled American women. I start by describing the labor force participation and usual hours worked per week in the past year (Table 1). As the household production demands may differ between households with children versus households without children, following East and Velasquez (2019), I also explore the results on subsamples of women with children (ages 0-18) and women with

[5] http://www.ncsl.org/research/immigration/everify-faq.aspx

[6] The ACS is the preferred dataset for this article because the ACS is mandatory, and therefore response at the unit and item level is higher in the ACS than the Current Population Survey.

[7] The results are robust to the use of the sample people aged 25-64.

children under 5 living at home.

Time Use Data.— I use the 2005-2017 American Time Use Survey (ATUS) Integrated Public Use Microdata Series data (Hofferth et al., 2019) to investigate the changes in women's time use.[8] The ATUS sample is selected randomly from households that are completing their participation in the Current Population Survey (CPS). On average, individuals are sampled between two and five months after the last CPS interview for the ATUS household. The respondents' activities are over a 24-hour period. I convert this to weekly measures by multiply by 7 to be compatible with ACS measures.

Consumption Data.— I use the Consumer Expenditure Survey (CEX), a nationwide household survey conducted by the U.S. Bureau of Labor Statistics, to measure expenditures on household services during the 2005-2017 period. I try to construct a sample from the CEX as closely comparable as possible to the ACS sample. I estimate the model with individual-level data using the sample weights in ATUS and CEX, as the sample sizes are smaller in these data sets.

As Table 1 shows, socioeconomic characteristics like age, race, marital status, number of children, and number of children younger than 5 are closely comparable across ACS, ATUS, and CEX. Table 1 also shows that, in comparison with men, women are less likely to participate in the labor force, and more likely to spend time on household activities. For example, 82% of high-skilled women work, while 91% of high-skilled men work. On average, high-skilled citizen women spend 15.5 hours on household activities, while high-skilled citizen men spend 10.2 hours weekly to maintain their household.

[8] I construct the ATUS sample as similar as possible to the ACS sample: U.S. citizen women with a college degree or more aged 20-64

3 Empirical Framework

To examine the causal effect of E-Verify on labor market outcomes of high-skilled women, I exploit both the staged rollout of E-Verify. I estimate a difference-in-differences model comparing areas that adopted E-Verify to areas that did not adopt E-Verify but were trending similarly in the pre-period. The primary model specification was as follows:

$$Y_{st} = \alpha + \sigma \textit{E-Verify}_{st} + \textit{state}_s + \textit{year}_t + \beta X_{st} + Z_{st} + Z_{s00} \cdot t + \epsilon_{st} \tag{1}$$

where s is state and t is year. Y_{st} is the outcome of interest. Y_{st} is the labor force participation rate or usual hours worked. In all specifications, I exclude early adoption states since E-Verify was implemented in those states early and selection could have played a role in activation (Miles and Cox, 2014; Alsan and Yang, 2018).[9]

In the specification above, $\textit{state}_s$ and $\textit{year}_t$ are state and year fixed effects to account for state-specific policies or economic shocks that might affect the labor supply. $\textit{E-Verify}_{st}$ is a binary variable indicating whether the state adopts E-Verify during that particular year.[10] This is a difference between my identification strategy and the one used in East and Velasquez (2019). Specifically, the difference-in-differences variable in East and Velasquez (2019) is a continuous variable between 0 and 1 while mine is a binary variable.

Following Cortes and Tessada (2011), X_{st} is the average socioeconomic characteristics in each state-year cell of: age, age squared, number of children, number of children under age 5, indicators for educational attainment, black dummy, married dummy, and metro dummy.[11] The vector Z_{st} contains state-level controls: housing price and unemployment rate to adjust

[9] The excluding states are Arizona, Georgia, Mississippi, Missouri, Oklahoma, and South Carolina.

[10] I set the treatment variable $\textit{E-Verify}_{st}$ to one if state s has E-Verify program in place by August of year t. As we don't know the month of the interview in ACS, I have explored the sensitivity to alternative timing assumptions. As shown in Table (A.3), the results are qualitatively similar across all specifications.

[11] Black et al. (2014) found that commuting time has a negative effect on labor supply of married women. The results are robust if I additionally control for average commute time.

for the large effect of the 2007-09 U.S. recession on labor markets. Following Hoynes and Schanzenbach (2009), $Z_{s00} \times t$ are interactions of state characteristics in 2000 with linear time trends. Z_{s00} includes state-level labor force participation rate, the share of the state that are immigrants, black, married, have children, have young children, reside within a metropolitan area, work more than 50 and 60 hours, have a high school diploma, some college, or college degree. All specifications are estimated using state population weights, and standard errors are clustered at the state level (Bertrand et al., 2004).

Identification.— As is standard in difference-in-differences models, my identification relies on the common trend assumption that in the absence of the policy, the labor supply of women in treated and control states evolve in parallel. I do a number of things to provide support to this identification assumption.

First, I conduct an event study to see if there is a systematic difference in high-skilled citizen women labor supply before the E-Verify implementation across states. Specifically, the estimating event study model for outcome Y is:

$$Y_{st} = \alpha + \textit{E-Verify}_{st}\left[\sum_{r=-4}^{-2} \pi_r 1_{rt} + \sum_{r=0}^{3} \pi_r 1_{rt}\right] + state_s + year_t + \beta X_{st} + Z_{st} + Z_{s00} \cdot t + \epsilon_{st} \quad (2)$$

The coefficients of interest, π_r, identify the effect of E-Verify on labor supply of high-skilled citizen women relative to the omitted group, r = -1. All control variables are the same as in Equation (1). The event study results in Figure 3 suggest that there were no differences across states in the labor supply before E-Verify was adopted. Moreover, one can see a significant negative effects of E-Verify on labor supply after E-Verify implementation.

Second, as a test for endogenous policy implementation, I attempt to predict the implementation of E-Verify using low-skilled immigrant share of labor force in Table A.1. Significant coefficients on the low-skilled immigrant share of labor force/total population would indicate that the policies were implemented in response to pre-existing trends in the share of low-skilled immigrants, and this would limit the causal interpretation of my results. I find that the coefficients on the share of low-skilled immigrant are generally insignificant. This serves as strong evidence that E-Verify was not endogenously implemented in response to particularly high low-skilled immigrant share, which supports the causal interpretation of my labor supply results.

4 Results

4.1 Effects on Labor supply of High-Skilled Women

In light of my proposed economic channels, I expect sigma to have a negative sign and be increasing in magnitude as the domestic burdens of the household increase, in particular with the introduction of a dependent. I estimate model (1) separately for all women, mothers, and mothers of young children.

Table 2 presents estimates of the effects of E-Verify on the labor supply of high-skilled citizen women of equation (1) above. Column (1) of Table 2 shows the results for all citizen women, column (2) shows the impact on mothers, column (3) shows the impact on mothers of young children. As observed in Table 2, the E-Verify coefficients (σ) exhibit a clear increasing pattern as we move from column (1) to column (3).

Full sample of highly skilled women.— The results in column (1) of Panel A show that the adoption of E-Verify decreases the labor force participation of high-skilled women by 0.4% (=0.003/0.823) relative to the sample mean. The adoption of E-Verify also reduces the time of this group's work by 0.16 hours or 10 minutes per week (0.49%[12] relative to the sample mean) as showed in Panel B.

Mothers.— The results for mothers in column (2) and (3) are larger than the full sample. For mothers, their labor force participation reduces by 0.9% (=0.007/0.801), and for mothers

[12] (=0.160/32.96)

of children under 5, the reduction is 1.2% (=0.009/0.756). The results in columns (2) and (3) of Panel B indicate that E-Verify has a significant negative effect on the hours worked. Specifically, the implementation of E-Verify decreases usual hours worked of mothers by 0.26 hours or 16 minutes per week, which is 0.85% relative to the mean, while the reduction for mothers of young children is 0.37 hours or 22 minutes per week (1.3% relative to the sample mean).

4.2 Mechanisms

To test the hypothesis that a higher household services price is an important channel for the reduction in labor supply of high-skilled women, I present several results. First, I replicate the findings of Amuedo-Dorantes and Bansak (2014), extending the analysis by including 2013, 2014, 2015, 2016, and 2017. I confirm that E-Verify substantially decreases the labor supply of likely undocumented immigrants (Table 4). This result is also consistent with Orrenius and Zavodny (2015) whose found that "E-Verify are largely successful in achieving the goal of worsening labor market outcomes among unauthorized immigrants".

Second, using wage of household workers as a proxy for the price of outsourcing household services, I find evidence that E-Verify caused an increase in wage of household workers (Table 8) .

Third, using the CEX data, I test whether there are changes in consumption of household services. I expect spending on household services to decrease, as the prices of household services increase. My estimates are summarized in Table 7. Column (1) reports the estimation for the full sample of high-skilled female-headed household, column (2) for the subsample of mothers, and column (3) for mothers of young children. The results indicate that female-headed household, on average, spent \$76 less per year (\$1.46 per week) on housekeeping services. This is consistent with Cortes and Tessada (2011), who find that low-skilled immigration into the U.S. during 1980s and 1990s increases expenditures on housekeeping of high-skilled female-headed households. The magnitude of the estimate for households with children in column 2 suggests that E-Verify decreases household spending on housekeeping services by $110 per year. The presence of young children is an important factor that decides the need for household work. As confirmed by the theoretical model in Cortes and Tessada (2011), women with young children in the household are more likely to consume household services. This may be the reason that we do not find a statistically significant effect for female-headed household with young children in column (3).

Fourth, I find E-Verify increases time spent on housework of high-skilled citizen mothers. Specifically, I estimate a difference-in-differences model with the ATUS data with outcome variables are: time (hours per week) allocated to housework and childcare. The estimate results are presented in Table 3. In Column (2) for mothers, I find that college-educated mothers spent one hour more per week on housework when E-Verify is implemented. When I restrict the sample to women with young children in Column (3), the impact of E-Verify is larger. This is similar to the findings in Table 2. On average, mothers of young children spent an extra two hours per week on housework. Results in Panel B show that E-Verify does not affect time allocated to childcare. It is not surprising that E-Verify increases time spent on housework but does not have any effects time allocated to childcare since it shows the difference in which household tasks are more likely to be outsourced.[13]

Effects of E-Verify on High-Skilled Men.— So far, I argue that the decline in price of household services is likely to be the channel through which E-Verify affects the labor supply of high-skilled citizen women. However, there are alternative channels through which illegal immigrants can affect the labor supply of high-skilled workers. For example, low-skilled illegal immigrants and high-skilled workers are complementary in the labor market (Cortes and Tessada, 2011; Chassambouli and Peri, 2015). Using high-skilled men as a control group

[13] *Housework* measures time spent on housework, cleaning, home maintenance, and travel related to those activities. *Childcare* measures all time spent by the individual caring for, organizing and planning for children, and looking after children.

allows me to control for this alternative channel since high-skilled men are less likely to be affected by the changes in price of household services.[14]

The effects of E-Verify on labor supply and time use of high-skilled men are presented in Table 5 and Table 6, respectively. All the results are small in magnitude and statistically insignificant, confirming that high-skilled men have reacted less than comparable women to the implementations of E-Verify. These results give further evidence suggesting that E-Verify has important effects on the labor supply decision of high-skilled citizen women, at least partly due to the changes in the cost of outsourcing household services.

Taken together, these findings suggest that higher cost of household service is a likely explanatory channel.

4.3 Sensitivity Checks

Appendix A.1 contains several robustness checks, some of which have been referenced above.[15]

First, I follow suggestions in Goodman-Bacon (2019) to address potential concerns about the robustness of difference-in-differences (DD) with variation in treatment timing. Goodman-Bacon (2019) shows how the causal treatment effects resulting from a specification as the one in equation (1) are simply a weighted average of all the possible two-group/two-period DD estimators in the data. The author proposes using the DD decomposition theorem to illustrate the sources of variation and to eliminate comparisons between earlier and later E-Verify-adopting states.[16] Figure A.1 uses the DD decomposition theorem to illustrate the variation sources by plotting each 2x2 DD against its weight. Summing the weights on timing terms (the x's on Figure A.1) shows how much of the DD estimate comes from timing

[14]Indeed, high-skilled men spend less time in household production (10 vs 16 hours) and care for children (4 vs 9 hours). Thus they are less likely to change their time-use decisions in response to changes in the price of household services.

[15]The results of robustness checks are summarized in Table 10.

[16]See Goodman-Bacon (2018) for a detailed description about the DD decomposition theorem.

variation (7 percent[17]). The 2x2 terms that compare treated/untreated states (the closed triangles on Figure A.1) account for 93 percent of the estimate. The DD estimates using the DD decomposition theorem match closely to the baseline results, which suggests that bias resulting from time-varying treatment effects is not a big concern in my setting.[18]

Second, my results are robust to limiting the treatment groups to states that require E-Verify for all employers only (Table A.11), and to states that require E-Verify for state agencies, contractors, and subcontractors only (Table A.12). They are also robust to dropping California (Table A.9), dropping Colorado (Table A.10).[19]

Third, my results are robust to functional form choices. There were two intensity-levels E-Verify in the study period: (i) E-Verify is required for all employers and (ii) E-Verify is required for state agencies and public contractors only.[20] In my empirical specification, I do not consider a "hybrid" model that separates the types of E-Verify, I simply model the presence of E-Verify. I now present the results for a "hybrid" model (Amuedo-Dorantes and Bansak, 2014). Specifically, I estimate the following linear probability model:

$$Y_{st} = \alpha + \sigma \textit{E-Verify\_all}_{st} + \gamma \textit{E-Verify\_partial}_{st} + \delta_s + \delta_t + \beta X_{st} + Z_{st} + \epsilon_{ist} \tag{3}$$

where all specifications are the same as in equation (1) except $\textit{E-Verify\_all}_{st}$ is a binary variable equal to one if state s required E-Verify for all employers at time t, and $\textit{E-Verify\_partial}_{st}$ is an indicator variable describing whether state s only required E-Verify for state agencies

[17] Table A.16, column 1 weight: 3.5 + 3.5 = 7 percent.

[18] The reason for this is that the relative size of the never treated states is large. Cases in which the never treated group's relative size is smaller, I would probably find the significant changes in DD estimates using the DD decomposition theorem compared to the baseline model.

[19] California has the largest unauthorized immigrant population in 2016 according to an estimation by Pew Research Center. Colorado's E-Verify law became effective on 7 August 2006, and was amended on 13 May 2008 (created an alternative program for E-Verify so E-Verify is not mandated in Colorado). Source: https://en.wikipedia.org/wiki/E-Verify#Colorado

[20] There are six states that require E-Verify for all employers: AL, AZ, MS, NC, SC, TN. States that require E-Verify for state agencies and public contractors are: CO, FL, GA, ID, IN, LA, MI, MO, NE, OK, PA, TX, UT, VA, WV

and public contractors at time t. As shown in Table A.4, the results are very similar to the baseline model.

Fourth, my results are robust to including state-specific linear time trends to additionally control for state-specific unobservables that vary over time (Table A.6) (Wolfers, 2006; Lee and Solon, 2011).[21] The results are also robust to including interactions of state pre-treatment characteristics with time fixed effects (Table A.5).

Fifth, as states that adopted E-Verify during 2006-2008 may be highly selected, I test the sensitivity of the results to including these states. Table A.8 provides these estimates and I find the results are very similar to the baseline model.

Sixth, there may be other immigration policy changes like the Secure Communities programs and 287(g) agreements that could affect the population of undocumented immigrants. I collect the information about the implementation of Secure Communities and 287(g) and create fixed effects for those policy implementations. Including these controls does not change my main effect (Table A.7).

Lastly, the results could be biased if high-skilled citizen women migrate in responding to E-Verify. Table A.14 presents the results of a model that estimate the impacts of E-Verify on the migration rates of high-skilled citizen women, high-skilled citizen men, low-skilled non-citizens, and non-citizen household workers. Outcome variables are the migration rates for each group which is defined as the number of interstate movers per 10,000 people relative to the population in 2005. As observed in Table A.14, E-Verify implementations did not have a significant effect on the migration rates of high-skilled women with children and high-skilled women with young children.[22]

[21] Except that these time trends might be "over controlling" and in addition to absorbing pre-existing trends, they may also absorb part of the treatment effect so that some of the estimates are no longer significant.

[22] I would not consider migration of low-skilled immigrants as biasing my results as low-skilled migration in response to E-Verify implementations is part of the mechanism.

5 Conclusion

In this paper, I find that the adoption of E-Verify mandates reduces the labor supply of high-skilled citizen women: lower hours worked and labor force participation rate. The effect is stronger for mothers and mothers of young children. Specifically, undocumented immigrants are over-represented in household services[23], E-Verify decreases the hires of undocumented immigrants which may increase the price of household services, and these price increases can generate effects on the labor supply of high-skilled citizen women.

I presented suggestive evidence that changes in the price of household services probably is a crucial mechanism. First, it is well-studied in the literature that E-Verify has a negative effect on the labor supply of likely undocumented immigrants (Amuedo-Dorantes and Bansak, 2014; Orrenius and Zavodny, 2015). Second, using the wage of citizen household workers as a proxy for the cost of household production, I find statistically significant increases in this cost in response to E-Verify. Third, E-Verify increases time spent on household work among mothers and decreases amount of housekeeping services purchased on the market of female-headed households.

Overall, my findings provide evidence of spillover effects of the Employment verification system, which is designed to affect only undocumented immigrants, on native mothers' labor outcomes. My back-of-the-envelope estimates suggest \$6.09 billion (2018 dollars) in annual social costs from the reduction of high-skilled citizen women labor supply (Table 9). This social costs may be worth considering by states and by the federal government in debating and reforming immigration policy.

[23]Undocumented immigrants disproportionately work in household services as: maids, housekeeping cleaners, gardeners, and workers in dry cleaning and laundry services (Cortes and Tessada, 2011; Passel and Cohn, 2016)

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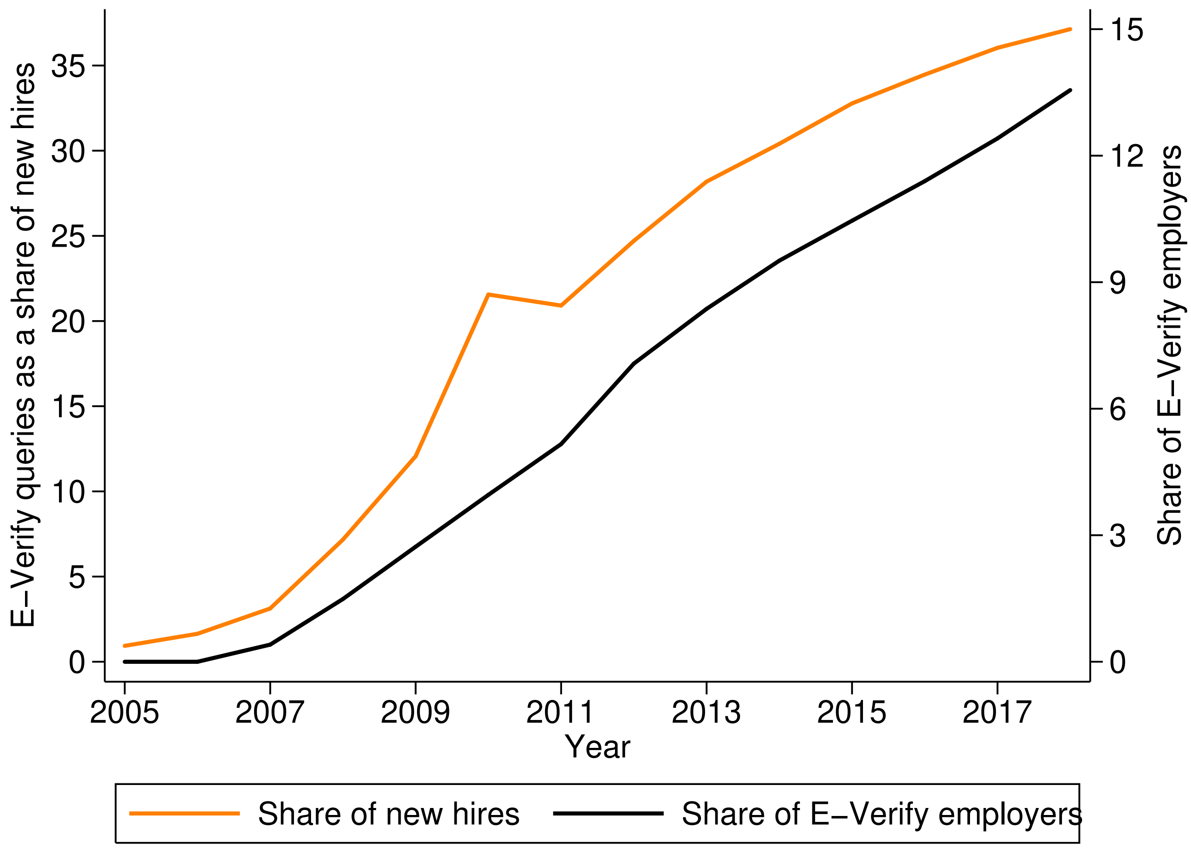
6 Figures

Figure 1: E-Verify Use Rate



Notes: Data are from U.S. Citizenship and Immigration Services (USCIS), Small Business Administration, Census Bureau, Westat, and Cato Institute. The orange line denotes E-Verify queries as a share of new hires. The black line denotes number of employers using E-Verify as a share of total employers. 2018 Hires based on 2016-2017 growth; 2018 queries based on 3 quarter of 2018.

Figure 2: E-Verify Implementation

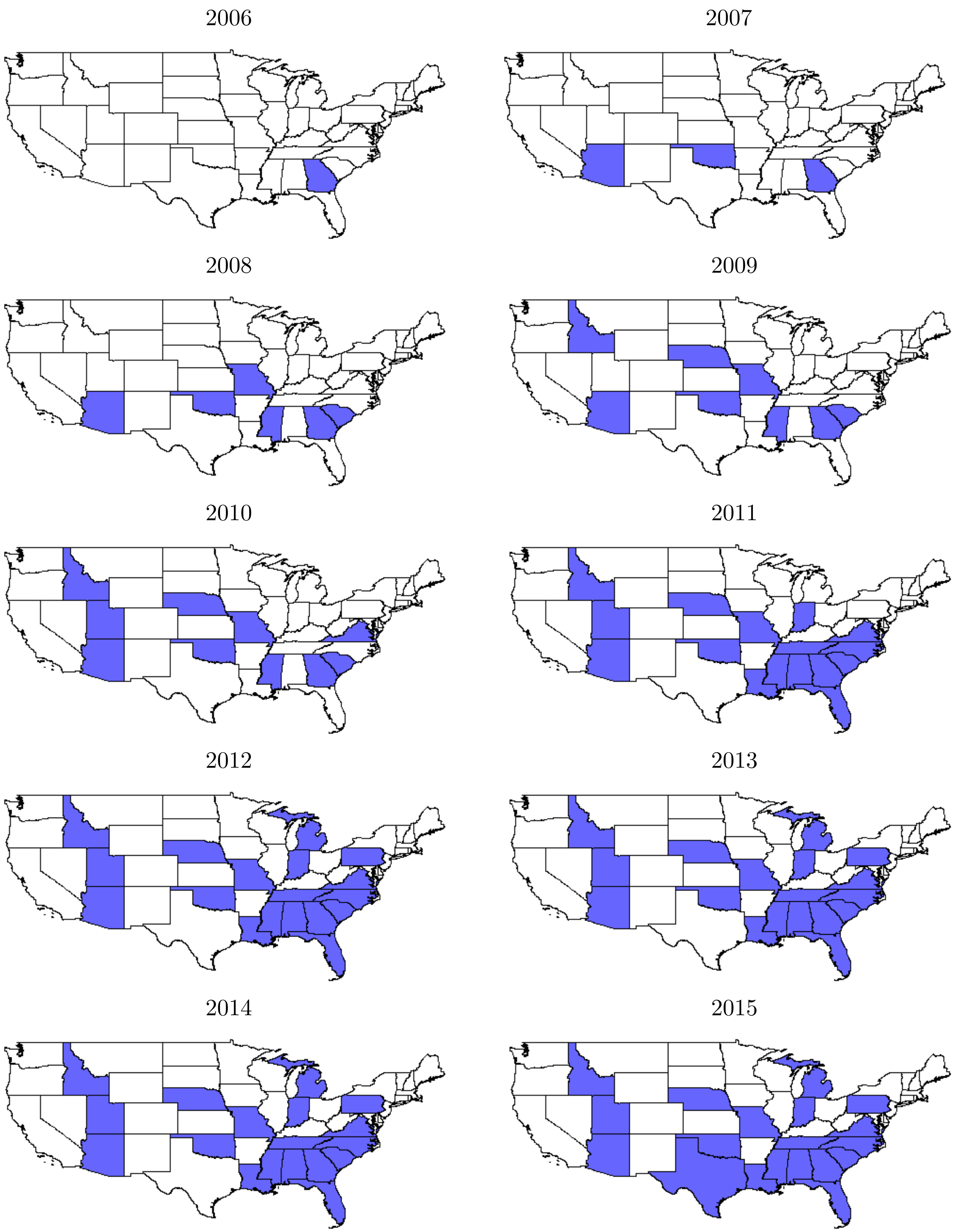
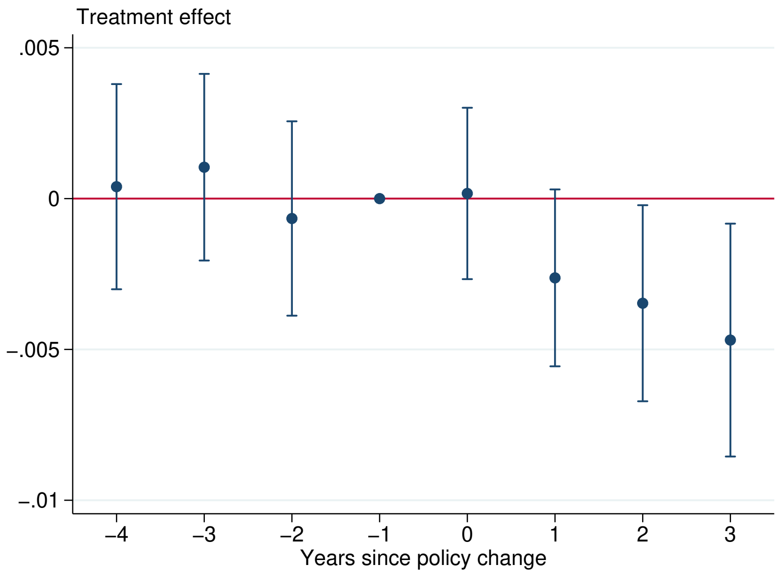
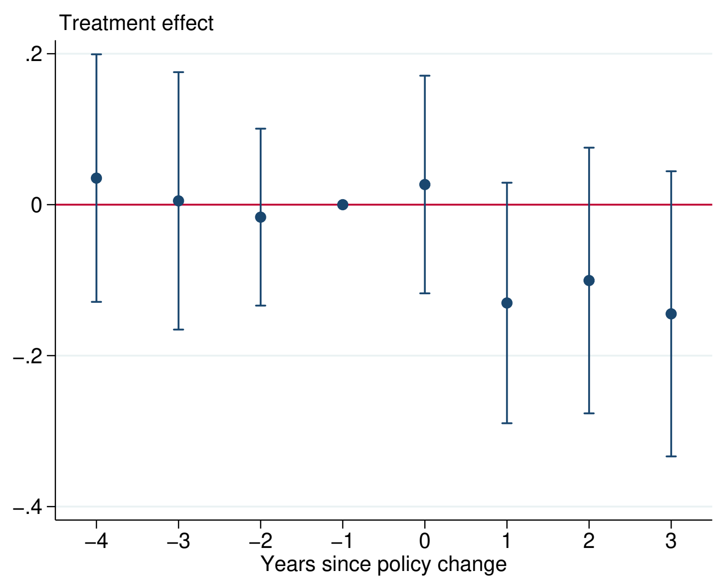


Figure 3: Event Study for High-Skilled Women's Labor Supply

(a) Labor force participation



(b) Hours worked



Notes: Data are from the 2005-2017 IPUMS ACS. I restrict the sample to U.S. citizen women with a college degree or more aged 20-64. All estimations include year fixed effects, state fixed effects, and demographic controls: age, age squared, black dummy, married dummy, reside within a metropolitan area dummy, number of children, number of children under age 5, educational attainment. 2000 state-level variables (labor force participation rate, the share of the state that are immigrants, black, married, have children, have young children, reside within a metropolitan area, work more than 50 and 60 hours, have a high school diploma, some college, or college degree), each interacted with a linear time trend. State-level controls include housing price and unemployment rate. All statistics are calculate using state population weights. Standard errors are clustered at the state level. Whiskers show 95% confidence interval.

7 Tables

Table 1: Summary Statistics

	All women	Women with children	Women with children under 5	All men
Panel A. American community survey				
Labor force participation	0.82	0.80	0.76	0.91
Usual hours worked	33.00	31.35	29.21	40.81
Usual hours worked $\mid H > 0$	38.73	37.65	36.67	44.13
Work at least 50 hrs.	0.15	0.13	0.10	0.30
Work at least 60 hrs.	0.044	0.036	0.026	0.11
Age	42.19	42.33	34.31	43.56
Black	0.09	0.09	0.08	0.07
Married	0.61	0.81	0.89	0.65
Number of children	0.85	1.83	1.95	0.83
Number of children Under 5	0.19	0.42	1.30	0.19
Sample size	3,512,953	1,641,885	520,197	3,021,392
Panel B. American time use survey				
Time spent on housework (hrs per week)	15.51	17.26	15.93	10.24
Time spent on childcare (hrs per week)	8.90	15.40	25.09	4.35
Age	42.08	41.67	34.40	43.03
Black	0.08	0.08	0.07	0.07
Married	0.68	0.86	0.92	0.68
Number of children	1.06	1.94	2.01	0.97
Number of children under 5	0.27	0.48	1.32	0.23
Sample size	510,810	329,032	130,565	341,001
Panel C. Consumer expenditure survey				
Expenditure on housekeeping services	524.65	602.70	451.60	530.17
Age	46.75	42.02	35.25	47.45
Black	0.05	0.05	0.02	0.03
Married	0.67	0.85	0.93	0.78
Percent having children in household	0.46	1	1	0.46
Percent having children under 5 in HH	0.11	0.23	1	0.11
Sample Size	5,205	2,479	553	5,405

Notes: The sample includes U.S. citizen with a college degree or more aged 20-64. Data from the 2005-2017 IPUMS ACS, IPUMS ATUS, and CEX. All statistics are calculated using sample weights.

Table 2: Effect of E-Verify on Labor Supply of High-Skilled Women

	Full sample	With chidlren	With young children
	(1)	(2)	(3)
Panel A. Labor force participation			
E-Verify (σ)	-0.003***	-0.007***	-0.009***
	(0.001)	(0.002)	(0.003)
Mean of dep. var.	0.823	0.801	0.756
Observations	585	585	585
Panel B. Hours worked			
E-Verify (σ)	-0.160***	-0.262**	-0.366**
	(0.057)	(0.104)	(0.153)
Mean of dep. var.	32.96	30.93	29.19
Observations	585	585	585
Demographics	X	X	X
Year and state fixed effects	X	X	X
2000 state vars $\times$ linear time	X	X	X

Notes: Each parameter is from a separate regression of the outcome variables: labor force participation and hours worked. Data are from the 2005-2017 IPUMS ACS. I restrict the sample to U.S. citizen women with a college degree or more aged 20-64. All estimations include year fixed effects, state fixed effects, and demographic controls: age, age squared, black dummy, married dummy, reside within a metropolitan area dummy, number of children, number of children under age 5, educational attainment. 2000 state-level variables (labor force participation rate, the share of the state that are immigrants, black, married, have children, have young children, reside within a metropolitan area, work more than 50 and 60 hours, have a high school diploma, some college, or college degree), each interacted with a linear time trend. State-level controls include housing price and unemployment rate. All results are estimated using state population weights. Standard errors are clustered at the state level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 3: Effect of E-Verify on Time Use of High-Skilled Women

	Full sample	With chidlren	With young children
	(1)	(2)	(3)
Panel A. Housework time			
E-Verify (σ)	0.853*	1.011**	2.109**
	(0.441)	(0.431)	(0.891)
Mean of dep. var.	8.77	9.62	8.64
Observations	460,050	297,948	118,609
Panel B. Childcare time			
E-Verify (σ)	0.432	0.446	-0.416
	(0.553)	(1.020)	(1.481)
Mean of dep. var.	8.98	15.47	25.18
Observations	460,050	297,948	118,609
Demographics	X	X	X
Year and state fixed effects	X	X	X
2000 state vars × linear time	X	X	X

Notes: Each parameter is from a separate regression of the outcome variables: labor force participation and hours worked. Data are from the 2005-2017 IPUMS ATUS. I restrict the sample to U.S. citizen women with a college degree or more aged 20-64. All estimations include year fixed effects, state fixed effects, and demographic controls: age, age squared, black dummy, married dummy, reside within a metropolitan area dummy, number of children, number of children under age 5, educational attainment. 2000 state-level variables (labor force participation rate, the share of the state that are immigrants, black, married, have children, have young children, reside within a metropolitan area, work more than 50 and 60 hours, have a high school diploma, some college, or college degree), each interacted with a linear time trend. State-level controls include housing price and unemployment rate. All results are estimated using state population weights. Standard errors are clustered at the state level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 4: Effect of E-Verify on Labor Supply of Low-Skilled Likely Undocumented Immigrants

	Low-skilled Hispanic immigrants	Undocumented status imputed using Borjas's method
Panel A: Labor force participation		
E-Verify (σ)	-0.009	-0.016*
	(0.012)	(0.009)
Mean of dep. var.	0.746	0.765
Observations	577	583
Panel B: Usual hours worked		
E-Verify (σ)	-0.869**	-0.197
	(0.403)	(0.290)
Mean of dep. var.	29.82	39.38
Observations	577	583
Demographics	X	X
Year and state fixed effects	X	X
2000 state vars $\times$ linear time	X	X

Notes: Each parameter is from a separate regression of the outcome variables: labor force participation and hours worked. Data are from the 2005-2017 IPUMS ACS. I restrict the sample to people aged 20-64. All estimations include year fixed effects, state fixed effects, and demographic controls: age, age squared, black dummy, married dummy, reside within a metropolitan area dummy, number of children, number of children under age 5, educational attainment. 2000 state-level variables (labor force participation rate, the share of the state that are immigrants, black, married, have children, have young children, reside within a metropolitan area, work more than 50 and 60 hours, have a high school diploma, some college, or college degree), each interacted with a linear time trend. State-level controls include housing price and unemployment rate. All results are estimated using state population weights. Standard errors are clustered at the state level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 5: Effect of E-Verify on Labor Supply of High-Skilled Men

	Full sample	With chidlren	With young children
	(1)	(2)	(3)
Panel A. Labor force participation			
E-Verify (σ)	-0.001	0.001	0.001
	(0.002)	(0.001)	(0.001)
Mean of dep. var.	0.912	0.969	0.974
Observations	585	585	585
Panel B. Hours worked			
E-Verify (σ)	-0.153	-0.083	-0.087
	(0.122)	(0.089)	(0.130)
Mean of dep. var.	40.77	44.67	44.84
Observations	585	585	585
Demographics	X	X	X
Year and state fixed effects	X	X	X
2000 state vars $\times$ linear time	X	X	X

Notes: Each parameter is from a separate regression of the outcome variables: labor force participation and hours worked. Data are from the 2005-2017 IPUMS ACS. I restrict the sample to U.S. citizen men with a college degree or more aged 20-64. All estimations include year fixed effects, state fixed effects, and demographic controls: age, age squared, black dummy, married dummy, reside within a metropolitan area dummy, number of children, number of children under age 5, educational attainment. 2000 state-level variables (labor force participation rate, the share of the state that are immigrants, black, married, have children, have young children, reside within a metropolitan area, work more than 50 and 60 hours, have a high school diploma, some college, or college degree), each interacted with a linear time trend. State-level controls include housing price and unemployment rate. All results are estimated using state population weights. Standard errors are clustered at the state level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 6: Effect of E-Verify on Time Use of High-Skilled Men

	Full sample	With chidlren	With young children
	(1)	(2)	(3)
Panel A. Housework time			
E-Verify (σ)	0.138	0.308	0.537
	(0.416)	(0.420)	(0.839)
Mean of dep. var.	6.23	6.21	5.45
Observations	309,427	181,563	71,307
Panel B. Childcare time			
E-Verify (σ)	0.164	-0.075	-0.191
	(0.332)	(0.645)	(1.031)
Mean of dep. var.	4.34	8.46	13.75
Observations	309,427	181,563	71,307
Demographics	X	X	X
Year and state fixed effects	X	X	X
2000 state vars $\times$ linear time	X	X	X

Notes: Each parameter is from a separate regression of the outcome variables: labor force participation and hours worked. Data are from the 2005-2017 IPUMS ATUS. I restrict the sample to U.S. citizen men with a college degree or more aged 20-64. All estimations include year fixed effects, state fixed effects, and demographic controls: age, age squared, black dummy, married dummy, reside within a metropolitan area dummy, number of children, number of children under age 5, educational attainment. 2000 state-level variables (labor force participation rate, the share of the state that are immigrants, black, married, have children, have young children, reside within a metropolitan area, work more than 50 and 60 hours, have a high school diploma, some college, or college degree), each interacted with a linear time trend. State-level controls include housing price and unemployment rate. All results are estimated using state population weights. Standard errors are clustered at the state level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 7: E-Verify and Consumption of Housekeeping Services of High-Skilled Women

	Full sample	With chidlren	With young children
	(1)	(2)	(3)
Dependent variable: Housekeeping service expenditure			
E-Verify (σ)	-70.460**	-125.667**	-87.530
	(29.748)	(48.368)	(67.893)
Mean of dep. var.	526.35	607.14	443.48
Observations	5,056	2,404	535
Demographics	X	X	X
Year and state fixed effects	X	X	X
2000 state vars $\times$ linear time	X	X	X

Notes: Data are from the 2005-2017 Consumer Expenditure Survey. The sample includes U.S. citizen women with a college degree or more aged 20-64. All estimations include year fixed effects, state fixed effects, and demographic controls: age, age squared, black dummy, married dummy, reside within a metropolitan area dummy, number of children, number of children under age 5, educational attainment. 2000 state-level variables (labor force participation rate, the share of the state that are immigrants, black, married, have children, have young children, reside within a metropolitan area, work more than 50 and 60 hours, have a high school diploma, some college, or college degree), each interacted with a linear time trend. State-level controls include housing price and unemployment rate. All results are estimated using sample weights. Standard errors are clustered at the state level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 8: Effect of E-Verify on Low-Skilled Household Worker's Total Wages

	All low-skilled household workers	Low-skilled citizen household workers	Low-skilled non-citizen household workers
Dependent variable: Log total wage of HH workers			
E-Verify (σ)	0.065***	0.066**	0.042
	(0.021)	(0.025)	(0.027)
Mean of dep. var.	9.44	9.48	9.34
Observations	59,898	44,344	15,554
Demographics	X	X	X
Year and state fixed effects	X	X	X

Notes: Each parameter is from a separate regression of the outcome variable: log total wage of low-skilled household workers. Data are from the 2005-2017 IPUMS ACS. The sample includes people aged 20-64 who report working in household service occupation or industry. All estimations include year fixed effects, state fixed effects, and demographic controls: age, age squared, black dummy, married dummy, reside within a metropolitan area dummy, number of children, number of children under age 5, educational attainment. State-level controls include housing price and unemployment rate. All results are estimated using sample weights. Standard errors are clustered at the state level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 9: Social cost calculation to the U.S. from E-Verify's High-skilled Women Labor Supply Reduction

Average hours worked decreased per week	0.16 hour (Column 1, Table 2)
Average hours worked decreased per year	8.32 hours (= 0.16h×52weeks)
Average annual wage of a college-educated woman	$51,600 (Census Bureau report 2018)
Average hourly wage of college-educated women	$24.8 (= $51,600 / (40h×52w))
Number of women with college degree	29.5 million (Pew research data collected from BLS)
Annual social cost (2018 dollars)	$6.09 billion (=29.5 million × $24.8 × 8.32h)

Notes: Data from Pew Research Center, U.S. Census Bureau, and U.S. Bureau of Labor Statistics

Table 10: Robustness Checks

	All women		Women with children		Women with children under 5	
Specification	(1) LFP	(2) Hours worked	(3) LFP	(4) Hours worked	(5) LFP	(6) Hours worked
(1) Baseline	-0.003	-0.160	-0.007	-0.262	-0.009	-0.366
	(0.001)	(0.057)	(0.002)	(0.104)	(0.003)	(0.153)
(2) Alternative timing specifications	-0.003	-0.130	-0.007	-0.260	-0.010	-0.370
	(0.001)	(0.052)	(0.002)	(0.108)	(0.003)	(0.155)
(3) Stacked DD (Goodman-Bacon, 2019)	-0.002	-0.191	-0.007	-0.260	-0.010	-0.370
Additionally control for:						
(3) Pre-treatment state characteristics × time FE	-0.003	-0.160	-0.006	-0.261	-0.009	-0.389
	(0.001)	(0.059)	(0.002)	(0.109)	(0.004)	(0.159)
(4) State-specific linear time trends	-0.004	-0.145	-0.009	-0.200	-0.011	-0.234
	(0.001)	(0.070)	(0.003)	(0.148)	(0.004)	(0.221)
(5) Secure Communities & 287(g)	-0.003	-0.159	-0.007	-0.269	-0.009	-0.368
	(0.001)	(0.058)	(0.002)	(0.106)	(0.003)	(0.155)
(6) Including early adoption states	-0.003	-0.153	-0.006	-0.233	-0.009	-0.336
	(0.001)	(0.046)	(0.002)	(0.094)	(0.003)	(0.132)
Excluding:						
(7) California	-0.003	-0.161	-0.008	-0.303	-0.011	-0.414
	(0.001)	(0.059)	(0.002)	(0.094)	(0.003)	(0.147)
(8) Colorado	-0.005	-0.328	-0.009	-0.514	-0.014	-0.743
	(0.001)	(0.088)	(0.002)	(0.153)	(0.003)	(0.194)
(9) States that require E-Verify for all employers	-0.002	-0.180	-0.006	-0.277	-0.008	-0.380
	(0.001)	(0.055)	(0.002)	(0.107)	(0.003)	(0.169)

Note: See Appendix A.1 for details.

A Appendix

A.1 Additional Tables

Table A.1: Attempting to Predict E-Verify Implementation

	Dependent variable: Dummy E-Verify			
Low-skilled immigrant share of labor force	-1.487 (5.381)			
Low-skilled immigrant share of total population		-3.095 (7.067)		
Immigrant share of labor force			0.231 (4.238)	
Immigrant share of total population				-1.876 (5.032)
Observations	585	585	585	585

Notes: Data are from the 2005-2017 IPUMS ACS. I restrict the sample to working-age 20-64. All estimations include year fixed effects, state fixed effects, and demographic controls: age, age squared, black dummy, married dummy, reside within a metropolitan area dummy, number of children, number of children under age 5, educational attainment. 2000 state-level variables (labor force participation rate, the share of the state that are immigrants, black, married, have children, have young children, reside within a metropolitan area, work more than 50 and 60 hours, have a high school diploma, some college, or college degree), each interacted with a linear time trend. State-level controls include housing price and unemployment rate. All results are estimated using state population weights. Standard errors are clustered at the state level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A.2: Effect of E-Verify on Labor Supply of High-Skilled Women, Additional Outcomes

	All women	Women with children	Women with children under 5
Panel A: Work at least 50 hours			
E-Verify (σ)	-0.002	-0.004**	-0.006**
	(0.001)	(0.002)	(0.003)
Mean of dep. var.	0.145	0.120	0.101
Observations	585	585	585
Panel B: Work full time (>35 hours)			
E-Verify (σ)	-0.011***	-0.016***	-0.019***
	(0.002)	(0.004)	(0.006)
Mean of dep. var.	0.640	0.587	0.560
Observations	585	585	585
Panel C: Usual Hours Worked $\|H > 0$			
E-Verify (σ)	-0.137**	-0.254**	-0.339**
	(0.059)	(0.112)	(0.136)
Mean of dep. var.	38.704	37.240	36.641
Observations	585	585	585
Demographics	X	X	X
Year and state fixed effects	X	X	X
2000 state vars $\times$ linear time	X	X	X

Notes: Each parameter is from a separate regression of the outcome variables: work at least 50 hours, work full time, and hours worked given working positive hours. See Table 2 for full table notes.

Table A.3: Robustness to Alternative Timing Specifications

	All women	Women with children	Women with children under 5
Panel A: Labor force participation, January			
E-Verify (σ)	-0.003***	-0.007***	-0.010***
	(0.001)	(0.002)	(0.003)
Mean of dep. var.	0.823	0.801	0.756
Observations	585	585	585
Panel B: Labor force participation, April			
E-Verify (σ)	-0.002*	-0.006**	-0.009**
	(0.001)	(0.002)	(0.003)
Mean of dep. var.	0.823	0.801	0.756
Observations	585	585	585
Panel C: Hours worked, January			
E-Verify (σ)	-0.130**	-0.260**	-0.370**
	(0.052)	(0.108)	(0.155)
Mean of dep. var.	0.823	0.801	0.756
Observations	585	585	585
Panel D: Hours worked, April			
E-Verify (σ)	-0.115	-0.262**	-0.439**
	(0.075)	(0.129)	(0.178)
Mean of dep. var.	32.96	30.93	29.19
Observations	585	585	585

Notes: See Table 2 for full table notes.

Table A.4: Effect of E-Verify on Labor Supply of High-Skilled Women, Robustness to "Hybrid" Model

	All women	Women with children	Women with children under 5
Panel A: Labor force participation			
Required E-Verify for all employers (σ)	-0.011***	-0.015***	-0.019**
	(0.003)	(0.005)	(0.008)
Required E-Verify for state contractors only (γ)	-0.003**	-0.008***	-0.011***
	(0.001)	(0.002)	(0.004)
Mean of dep. var.	0.823	0.801	0.756
Observations	585	585	585
Panel B: Usual hours worked			
Required E-Verify for all employers (σ)	-0.324*	-0.439*	-0.801**
	(0.165)	(0.241)	(0.364)
Required E-Verify for state contractors only (γ)	-0.201***	-0.340***	-0.516**
	(0.067)	(0.111)	(0.213)
Mean of dep. var.	32.96	30.93	29.19
Observations	585	585	585
Demographics	X	X	X
Year and state fixed effects	X	X	X
2000 state vars × linear time	X	X	X

Notes: Each parameter is from a separate regression of the outcome variables: labor force participation and hours worked. Data are from the 2005-2017 IPUMS ACS. I restrict the sample to U.S. citizen women with a college degree or more aged 20-64. All estimations include year fixed effects, state fixed effects, and demographic controls: age, age squared, black dummy, married dummy, reside within a metropolitan area dummy, number of children, number of children under age 5, educational attainment. 2000 state-level variables (labor force participation rate, the share of the state that are immigrants, black, married, have children, have young children, reside within a metropolitan area, work more than 50 and 60 hours, have a high school diploma, some college, or college degree), each interacted with a linear time trend. State-level controls include housing price and unemployment rate. All results are estimated using state population weights. Standard errors are clustered at the state level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A.5: Effect of E-Verify on Labor Supply of High-Skilled Women, Robustness to Adjust for Interactions of Pre-Treatment State Characteristics with Time FE

	All women	Women with children	Women with children under 5
Panel A: Labor force participation			
E-Verify (σ)	-0.003***	-0.006***	-0.009**
	(0.001)	(0.002)	(0.004)
Mean of dep. var.	0.823	0.801	0.756
Observations	585	585	585
Panel B: Usual hours worked			
E-Verify (σ)	-0.160**	-0.261**	-0.389**
	(0.059)	(0.109)	(0.159)
Mean of dep. var.	32.96	30.93	29.19
Observations	585	585	585
Demographics	X	X	X
Year and state fixed effects	X	X	X
2000 state vars $\times$ linear time	X	X	X

Notes: Each parameter is from a separate regression of the outcome variables: labor force participation and hours worked. Data are from the 2005-2017 IPUMS ACS. I restrict the sample to U.S. citizen women with a college degree or more aged 20-64. All estimations include year fixed effects, state fixed effects, and demographic controls: age, age squared, black dummy, married dummy, reside within a metropolitan area dummy, number of children, number of children under age 5, educational attainment. 2000 state-level variables (labor force participation rate, the share of the state that are immigrants, black, married, have children, have young children, reside within a metropolitan area, work more than 50 and 60 hours, have a high school diploma, some college, or college degree), each interacted with a linear time trend. State-level controls include housing price and unemployment rate. All results are estimated using state population weights. Standard errors are clustered at the state level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A.6: Effect of E-Verify on Labor Supply of High-Skilled Women, Robustness to Adjust for State-Specific Linear Time Trends

	All women	Women with children	Women with children under 5
Panel A: Labor force participation			
E-Verify (σ)	-0.004***	-0.009***	-0.011**
	(0.001)	(0.003)	(0.004)
Mean of dep. var.	0.823	0.801	0.756
Observations	585	585	585
Panel B: Usual hours worked			
E-Verify (σ)	-0.145**	-0.200	-0.234
	(0.070)	(0.148)	(0.221)
Mean of dep. var.	32.96	30.93	29.19
Observations	585	585	585
Demographics	X	X	X
Year and state fixed effects	X	X	X
2000 state vars $\times$ linear time	X	X	X

Notes: Each parameter is from a separate regression of the outcome variables: labor force participation and hours worked. Data are from the 2005-2017 IPUMS ACS. I restrict the sample to U.S. citizen women with a college degree or more aged 20-64. All estimations include year fixed effects, state fixed effects, and demographic controls: age, age squared, black dummy, married dummy, reside within a metropolitan area dummy, number of children, number of children under age 5, educational attainment. 2000 state-level variables (labor force participation rate, the share of the state that are immigrants, black, married, have children, have young children, reside within a metropolitan area, work more than 50 and 60 hours, have a high school diploma, some college, or college degree), each interacted with a linear time trend. State-level controls include housing price and unemployment rate. All results are estimated using state population weights. Standard errors are clustered at the state level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.7: Robustness to Controlling for Secure Communities and 287(g) Agreements

	All women	Women with children	Women with children under 5
Panel A: Labor force participation			
E-Verify (σ)	-0.003***	-0.007***	-0.009***
	(0.001)	(0.002)	(0.003)
Mean of dep. var.	0.823	0.801	0.756
Observations	585	585	585
Panel B: Usual hours worked			
E-Verify (σ)	-0.159***	-0.269**	-0.368**
	(0.058)	(0.106)	(0.155)
Mean of dep. var.	32.96	30.93	29.19
Observations	585	585	585
Demographics	X	X	X
Year and state fixed effects	X	X	X
2000 state vars $\times$ linear time	X	X	X

Notes: Each parameter is from a separate regression of the outcome variables: labor force participation and hours worked. Data are from the 2005-2017 IPUMS ACS. I restrict the sample to U.S. citizen women with a college degree or more aged 20-64. All estimations include year fixed effects, state fixed effects, and demographic controls: age, age squared, black dummy, married dummy, reside within a metropolitan area dummy, number of children, number of children under age 5, educational attainment. 2000 state-level variables (labor force participation rate, the share of the state that are immigrants, black, married, have children, have young children, reside within a metropolitan area, work more than 50 and 60 hours, have a high school diploma, some college, or college degree), each interacted with a linear time trend. State-level controls include housing price and unemployment rate. All results are estimated using state population weights. Standard errors are clustered at the state level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A.8: Robustness to Including Early Adoption States (Full Sample)

	All women	Women with children	Women with children under 5
Panel A: Labor force participation			
E-Verify (σ)	-0.003***	-0.006***	-0.009***
	(0.001)	(0.002)	(0.003)
Mean of dep. var.	0.821	0.801	0.756
Observations	663	663	663
Panel B: Usual hours worked			
E-Verify (σ)	-0.153***	-0.233**	-0.336**
	(0.046)	(0.094)	(0.132)
Mean of dep. var.	32.96	31.03	29.22
Observations	663	663	663
Demographics	X	X	X
Year and state fixed effects	X	X	X
2000 state vars × linear time	X	X	X

Notes: Each parameter is from a separate regression of the outcome variables: labor force participation and hours worked. Data are from the 2005-2017 IPUMS ACS. I restrict the sample to U.S. citizen women with a college degree or more aged 20-64. All estimations include year fixed effects, state fixed effects, and demographic controls: age, age squared, black dummy, married dummy, reside within a metropolitan area dummy, number of children, number of children under age 5, educational attainment. 2000 state-level variables (labor force participation rate, the share of the state that are immigrants, black, married, have children, have young children, reside within a metropolitan area, work more than 50 and 60 hours, have a high school diploma, some college, or college degree), each interacted with a linear time trend. State-level controls include housing price and unemployment rate. All results are estimated using state population weights. Standard errors are clustered at the state level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A.9: Robustness to Dropping California

	All women	Women with children	Women with children under 5
Panel A: Labor force participation			
E-Verify (σ)	-0.003***	-0.008***	-0.011***
	(0.001)	(0.002)	(0.003)
Mean of dep. var.	0.823	0.801	0.756
Observations	572	572	572
Panel B: Usual hours worked			
E-Verify (σ)	-0.161***	-0.303***	-0.414***
	(0.059)	(0.094)	(0.147)
Mean of dep. var.	32.96	30.91	29.18
Observations	572	572	572
Demographics	X	X	X
Year and state fixed effects	X	X	X
2000 state vars $\times$ linear time	X	X	X

Notes: Each parameter is from a separate regression of the outcome variables: labor force participation and hours worked. Data are from the 2005-2017 IPUMS ACS. I restrict the sample to U.S. citizen women with a college degree or more aged 20-64. All estimations include year fixed effects, state fixed effects, and demographic controls: age, age squared, black dummy, married dummy, reside within a metropolitan area dummy, number of children, number of children under age 5, educational attainment. 2000 state-level variables (labor force participation rate, the share of the state that are immigrants, black, married, have children, have young children, reside within a metropolitan area, work more than 50 and 60 hours, have a high school diploma, some college, or college degree), each interacted with a linear time trend. State-level controls include housing price and unemployment rate. All results are estimated using state population weights. Standard errors are clustered at the state level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A.10: Robustness to Dropping Colorado

	All women	Women with children	Women with children under 5
Panel A: Labor force participation			
E-Verify (σ)	-0.005***	-0.009***	-0.014***
	(0.001)	(0.002)	(0.003)
Mean of dep. var.	0.823	0.801	0.757
Observations	572	572	572
Panel B: Usual hours worked			
E-Verify (σ)	-0.328***	-0.514***	-0.743***
	(0.088)	(0.153)	(0.194)
Mean of dep. var.	32.97	30.96	29.23
Observations	572	572	572
Demographics	X	X	X
Year and state fixed effects	X	X	X
2000 state vars × linear time	X	X	X

Notes: Each parameter is from a separate regression of the outcome variables: labor force participation and hours worked. Data are from the 2005-2017 IPUMS ACS. I restrict the sample to U.S. citizen women with a college degree or more aged 20-64. All estimations include year fixed effects, state fixed effects, and demographic controls: age, age squared, black dummy, married dummy, reside within a metropolitan area dummy, number of children, number of children under age 5, educational attainment. 2000 state-level variables (labor force participation rate, the share of the state that are immigrants, black, married, have children, have young children, reside within a metropolitan area, work more than 50 and 60 hours, have a high school diploma, some college, or college degree), each interacted with a linear time trend. State-level controls include housing price and unemployment rate. All results are estimated using state population weights. Standard errors are clustered at the state level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A.11: Robustness to Dropping States that Requiring E-Verify for All Employers

	All women	Women with children	Women with children under 5
Panel A: Labor force participation			
E-Verify (σ)	-0.002**	-0.006**	-0.008**
	(0.001)	(0.002)	(0.003)
Mean of dep. var.	0.824	0.801	0.757
Observations	546	546	546
Panel B: Usual hours worked			
E-Verify (σ)	-0.180***	-0.277**	-0.380**
	(0.055)	(0.107)	(0.169)
Mean of dep. var.	32.98	30.91	29.18
Observations	546	546	546
Demographics	X	X	X
Year and state fixed effects	X	X	X
2000 state vars $\times$ linear time	X	X	X

Notes: Each parameter is from a separate regression of the outcome variables: labor force participation and hours worked. Data are from the 2005-2017 IPUMS ACS. I restrict the sample to U.S. citizen women with a college degree or more aged 20-64. All estimations include year fixed effects, state fixed effects, and demographic controls: age, age squared, black dummy, married dummy, reside within a metropolitan area dummy, number of children, number of children under age 5, educational attainment. 2000 state-level variables (labor force participation rate, the share of the state that are immigrants, black, married, have children, have young children, reside within a metropolitan area, work more than 50 and 60 hours, have a high school diploma, some college, or college degree), each interacted with a linear time trend. State-level controls include housing price and unemployment rate. All results are estimated using state population weights. Standard errors are clustered at the state level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A.12: Robustness to Keeping Only States That Requiring E-Verify for All Employers As Treated

	All women	Women with children	Women with children under 5
Panel A: Labor force participation			
E-Verify (σ)	-0.011***	-0.013***	-0.019**
	(0.003)	(0.005)	(0.007)
Mean of dep. var.	0.827	0.803	0.761
Observations	429	429	429
Panel B: Usual hours worked			
E-Verify (σ)	-0.374**	-0.450*	-0.858**
	(0.168)	(0.238)	(0.317)
Mean of dep. var.	32.97	30.80	29.22
Observations	429	429	429
Demographics	X	X	X
Year and state fixed effects	X	X	X
2000 state vars × linear time	X	X	X

Notes: Each parameter is from a separate regression of the outcome variables: labor force participation and hours worked. Data are from the 2005-2017 IPUMS ACS. I restrict the sample to U.S. citizen women with a college degree or more aged 20-64. All estimations include year fixed effects, state fixed effects, and demographic controls: age, age squared, black dummy, married dummy, reside within a metropolitan area dummy, number of children, number of children under age 5, educational attainment. 2000 state-level variables (labor force participation rate, the share of the state that are immigrants, black, married, have children, have young children, reside within a metropolitan area, work more than 50 and 60 hours, have a high school diploma, some college, or college degree), each interacted with a linear time trend. State-level controls include housing price and unemployment rate. All results are estimated using state population weights. Standard errors are clustered at the state level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A.14: Effect of E-Verify on Interstate Migration Rates

	All high-skilled citizen women	High-skilled citizen women with kids	High-skilled citizen women kids under 5	All high-skilled citizen men	All low-skilled immigrants	Household workers immigrants
E-Verify (σ)	0.031	-0.246	0.456	0.765	0.625	5.391
	(0.593)	(0.444)	(1.415)	(1.436)	(2.396)	(6.455)
Mean of dep. var.	39.48	22.46	37.54	43.72	19.40	18.71
Observations	585	585	585	585	585	537
Demographics	X	X	X	X	X	X
Year and state fixed effects	X	X	X	X	X	X
2000 state vars $\times$ linear time	X	X	X	X	X	X

Notes: Dependent variables are the migration rates for each group which are defined as the number of interstate movers per 10,000 people relative to the population in 2005. Data are from the 2005-2017 IPUMS ACS. I restrict the sample to people aged 20-64. All estimations include year fixed effects, state fixed effects, and demographic controls: age, age squared, black dummy, married dummy, reside within a metropolitan area dummy, number of children, number of children under age 5, educational attainment. 2000 state-level variables (labor force participation rate, the share of the state that are immigrants, black, married, have children, have young children, reside within a metropolitan area, work more than 50 and 60 hours, have a high school diploma, some college, or college degree), each interacted with a linear time trend. State-level controls include housing price and unemployment rate. All results are estimated using sample weights. Standard errors are clustered at the state level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A.13: Effect of E-Verify on Labor Supply of High-Skilled Women, Individual-level Analysis

	All women	Women with children	Women with children under 5
Panel A: Labor force participation			
E-Verify (σ)	-0.003***	-0.006***	-0.010***
	(0.001)	(0.002)	(0.003)
Mean of dep. var.	0.825	0.804	0.757
Observations	3,168,036	1,479,384	468,338
Panel B: Usual hours worked			
E-Verify (σ)	-0.165***	-0.267**	-0.389***
	(0.054)	(0.100)	(0.143)
Mean of dep. var.	33.01	31.27	29.17
Observations	3,166,052	1,478,628	468,152
Demographics	X	X	X
Year and state fixed effects	X	X	X
2000 state vars × linear time	X	X	X

Notes: Each parameter is from a separate regression of the outcome variables: labor force participation and hours worked. Data are from the 2005-2017 IPUMS ACS. The sample includes high-skilled citizen women aged 20-64. All estimations include year fixed effects, state fixed effects, and demographic controls: age, age squared, black dummy, married dummy, reside within a metropolitan area dummy, number of children, number of children under age 5, educational attainment. 2000 state-level variables (labor force participation rate, the share of the state that are immigrants, black, married, have children, have young children, reside within a metropolitan area, work more than 50 and 60 hours, have a high school diploma, some college, or college degree), each interacted with a linear time trend. State-level controls include housing price and unemployment rate. All results are estimated using state population weights. Standard errors are clustered at the state level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

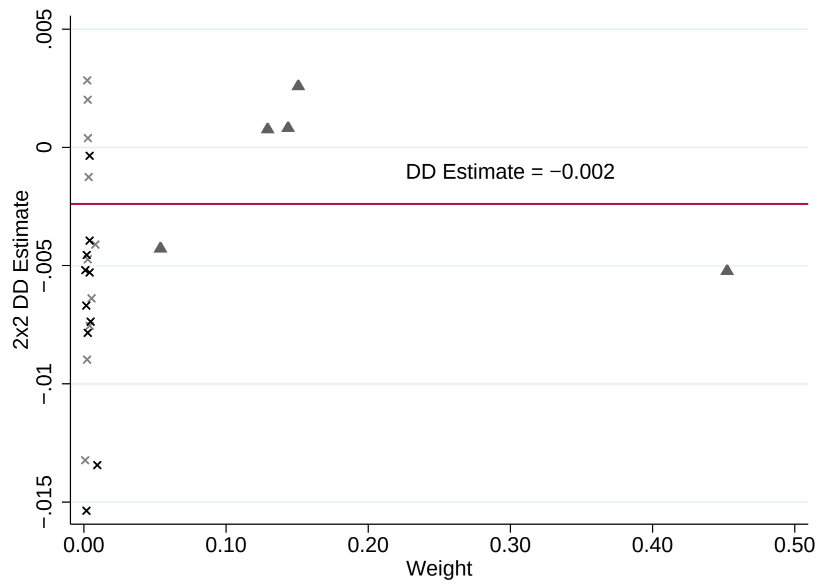
Table A.15: Effect of E-Verify on Labor Supply of High-Skilled Men, Individual-level Analysis

	All men	Men with children	Men with children under 5
Panel A: Labor force participation			
E-Verify (σ)	-0.002	0.000	0.001
	(0.002)	(0.001)	(0.001)
Mean of dep. var.	0.913	0.958	0.975
Observations	2,733,846	1,224,985	389,137
Panel B: Usual hours worked			
E-Verify (σ)	-0.149	-0.086	-0.061
	(0.133)	(0.109)	(0.113)
Mean of dep. var.	40.80	44.02	44.87
Observations	2,729,616	1,223,026	388,490
Demographics	X	X	X
Year and state fixed effects	X	X	X
2000 state vars $\times$ linear time	X	X	X

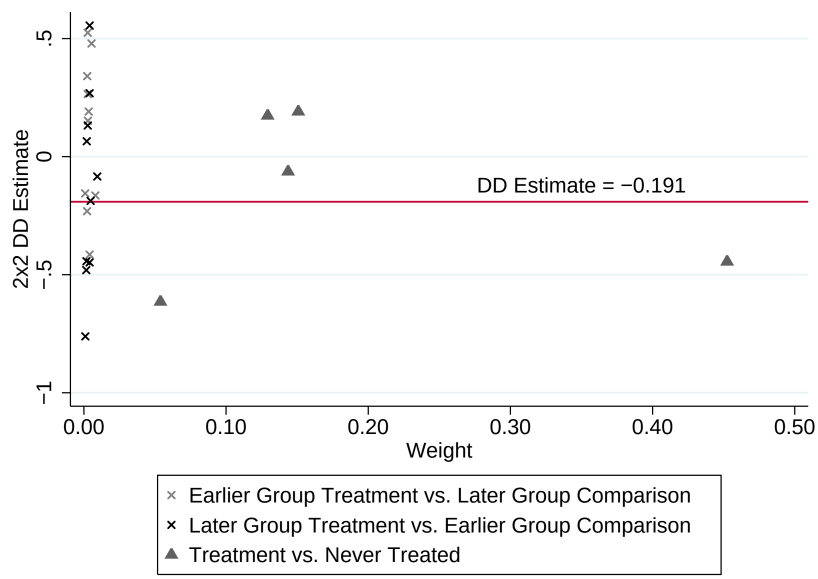
Notes: Each parameter is from a separate regression of the outcome variables: labor force participation and hours worked. Data are from the 2005-2017 IPUMS ACS. The sample includes high-skilled citizen men aged 20-64. All estimations include year fixed effects, state fixed effects, and demographic controls: age, age squared, black dummy, married dummy, reside within a metropolitan area dummy, number of children, number of children under age 5, educational attainment. 2000 state-level variables (labor force participation rate, the share of the state that are immigrants, black, married, have children, have young children, reside within a metropolitan area, work more than 50 and 60 hours, have a high school diploma, some college, or college degree), each interacted with a linear time trend. State-level controls include housing price and unemployment rate. All results are estimated using state population weights. Standard errors are clustered at the state level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Figure A.1: Goodman-Bacon DD Decomposition for E-Verify and Labor Supply, All Women

(a) Labor force participation



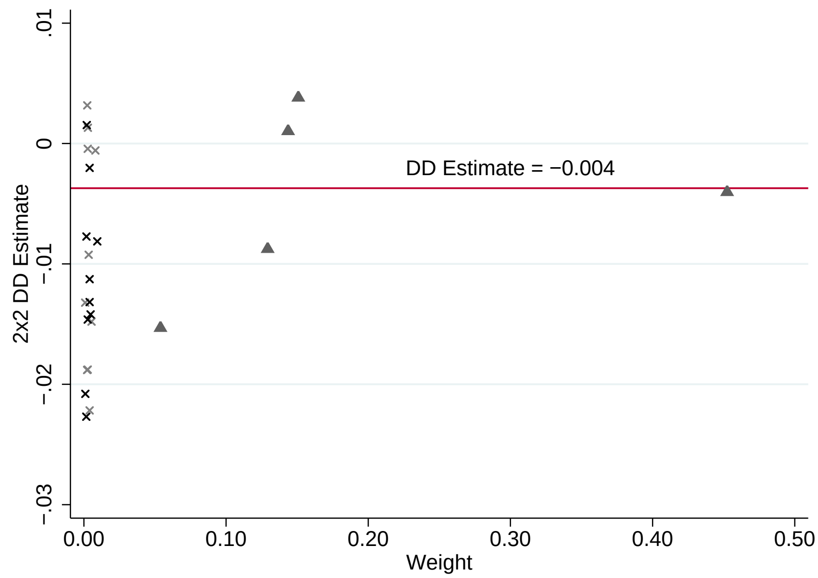
(b) Usual hours worked



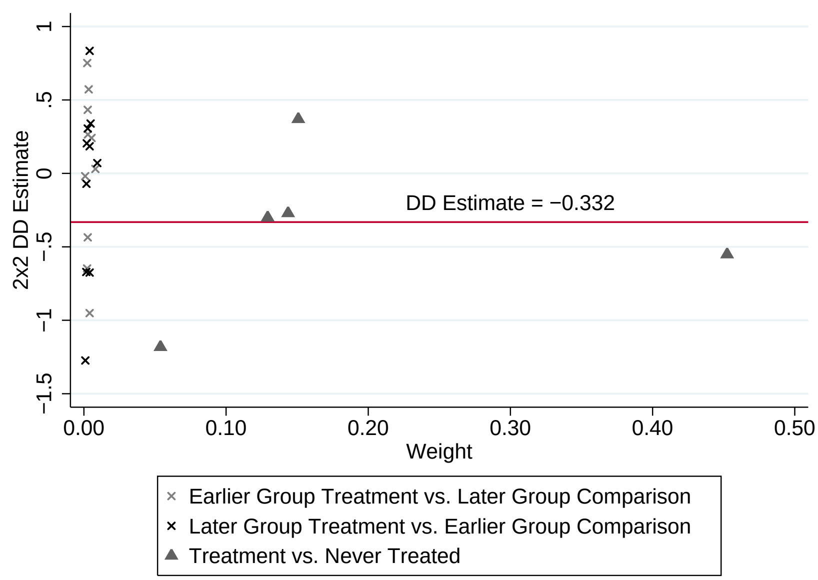
Notes: Data are from the 2005-2017 IPUMS ACS. The sample includes U.S. citizen women with a college degree or more aged 20-64. The figures plot each 2x2 DD components from the decomposition theorem in Goodman-Bacon (2019) against their weight. The bias resulting from time-varying effects (comparisons between earlier/later treated states are given very small weights. The red lines are the weighted average of all possible 2x2 DD estimators. All the DD estimates here match closely to the DD estimates using the baseline model in equation (1).

Figure A.2: Goodman-Bacon DD Decomposition for E-Verify and Labor Supply, Women with Children

(a) Labor force participation



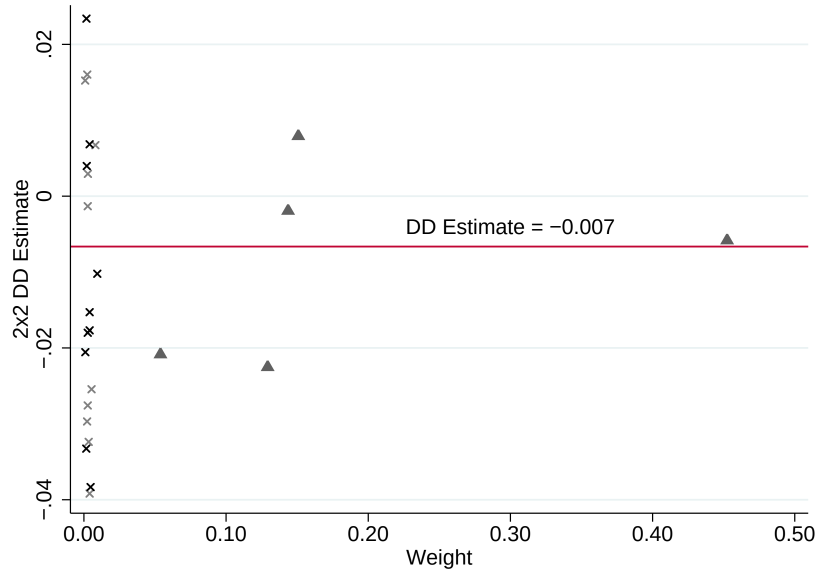
(b) Usual hours worked



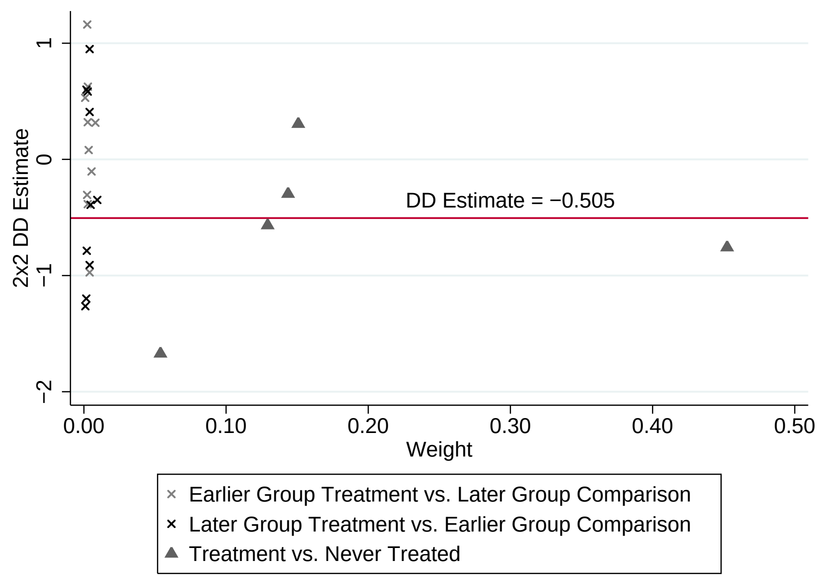
Notes: Data are from the 2005-2017 IPUMS ACS. The sample includes U.S. citizen women with a college degree or more aged 20-64. The figures plot each 2x2 DD components from the decomposition theorem in Goodman-Bacon (2019) against their weight. The red lines are the weighted average of all possible 2x2 DD estimators. All the DD estimates here match closely to the DD estimates using the baseline model in equation (1).

Figure A.3: Goodman-Bacon DD Decomposition for E-Verify and Labor Supply, Women with Children Under 5

(a) Labor force participation



(b) Usual hours worked



Notes: Data are from the 2005-2017 IPUMS ACS. The sample includes U.S. citizen women with a college degree or more aged 20-64. The figures plot each 2x2 DD components from the decomposition theorem in Goodman-Bacon (2019) against their weight. The red lines are the weighted average of all possible 2x2 DD estimators. All the DD estimates here match closely to the DD estimates using the baseline model in equation (1).

Table A.16: Goodman-Bacon DD Decomposition for E-Verify and Women Labor Supply

	All women		Women with children		Women with children under 5	
Panel A: Labor force participation						
Diff-in-diff Est	-0.002		-0.004		-0.007	
DD Comparison	Weight	Avg DD Est	Weight	Avg DD Est	Weight	Avg DD Est
Earlier T vs. Later C	0.035	-0.004	0.035	-0.009	0.035	-0.013
Later T vs. Earlier C	0.035	-0.008	0.035	-0.010	0.035	-0.013
T vs. Never treated	0.930	-0.002	0.930	-0.003	0.930	-0.006
Panel B: Usual hours worked						
Diff-in-diff Est	-0.191		-0.332		-0.505	
DD Comparison	Weight	Avg DD Est	Weight	Avg DD Est	Weight	Avg DD Est
Earlier T vs. Later C	0.035	0.084	0.035	0.019	0.035	0.070
Later T vs. Earlier C	0.035	-0.058	0.035	-0.066	0.035	-0.157
T vs. Never treated	0.930	-0.206	0.930	-0.360	0.930	-0.540

Notes: T = Treatment; C = Comparison. Data are from the 2005-2017 IPUMS ACS. The sample includes U.S. citizen women with a college degree or more aged 20-64.