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Chloe N. East
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Chloe N. East
University of Colorado Denver and IZA

Andrea Velasquez
University of Colorado Denver

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany
Phone: +49-228-3894-0
Email: publications@iza.org
www.iza.org

ABSTRACT

The Effect of Increasing Immigration Enforcement on the Labor Supply of High-Skilled Citizen Women[1]

Recent decades have seen a surge in local interior immigration enforcement. In this paper we examine a little discussed, but potentially important, spillover effect of enforcement policies: changes in high-skilled citizen women's labor supply due to changes in the cost of outsourcing household production. Undocumented immigrants disproportionately supply household services - e.g. as maids, cooks, child care workers, and gardeners - so the price of outsourcing these services is expected to rise in response to enforcement. Combining data on the timing and location of these enforcement policies, with data on labor supply from the American Community Survey over 2005-2012, we implement a difference-in-difference approach with location and year fixed effects to take advantage of the staggered implementation of these policies. We find that an increase in intensity of immigration enforcement in a local area reduced the labor supply of citizen college- educated women with children. Several results suggest that changes in the price of outsourcing are driving these results: 1) we see an increase in time spent on household production tasks among mothers in the American Time Use Survey, 2) we confirm that there is an increase in the wages of household workers, and 3) we see no similar effects for high-skilled men or women without children. This indicates there are important unintended consequences of enforcement policies on high-skilled citizen mothers' ability to work.

JEL Classification: F22, J2, K37, J16
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Corresponding author:
Chloe N. East
Department of Economics
University of Colorado, Denver
1380 Lawrence St.
Denver, CO 80217
USA
E-mail: chloe.east@ucdenver.edu

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1 Introduction

Roughly 11 million undocumented immigrants lived in the U.S. in 2015, making up 3.4% of the U.S. population (Krogstad, Passel and Cohn, 2017). While undocumented immigrants represent 5% of the total workforce in the U.S., they make up 22% of workers in private households, 7% of workers in personal and laundry services, and 24% of maids and housekeepers (Passel and Cohn, 2016). This reduces the cost of outsourcing household services, which can have important implications for the labor supply decisions of high-skilled workers (Cortes, 2008).

Over the last 15 years, many policies have been put in place to address the issue of undocumented immigrants by increasing both border and interior immigration enforcement. Moreover, interior enforcement action has devolved to state and local governments, while comprehensive federal immigration reform has continually stalled in Congress. Although an extensive literature has studied the impact of migratory flows on labor outcomes, the evidence on the effects of *enforcement policies* on citizens' wages and employment is more limited.[2]

In this paper we focus on the potential unintended consequences enforcement laws can have on the labor supply of high-skilled female workers due to undocumented immigrants disproportionate representation in household services work. Women may be particularly affected by changes in the cost of household work, as they both spend more time engaging in this type of work, and have a more elastic labor supply, when compared to men (Blau and Kahn, 2007; Pew Research Center, 2013). Additionally, high-skilled workers are expected to be the most affected, since they spend a larger fraction of their income on outsourcing

[2]Many studies on the effect of migration inflows on native wages and employment exist. For excellent reviews of the literature see Friedberg and Hunt (1995), Longhi, Nijkamp and Poot (2005), and Longhi, Nijkamp and Poot (2006). Previous studies on the labor market impacts of recent immigration enforcement policies in the U.S. have mostly focused on the direct effects on the migrant population. See Phillips and Massey (1999), Bansak and Raphael (2001), Orrenius and Zavodny (2009), Amuedo-Dorantes and Bansak (2014), and Orrenius and Zavodny (2015). The exception is East et al. (2018), who study the effects of Secure Communities on citizen and non-citizen employment outcomes.

household work (Cortes, 2008).[3] To test this hypothesis empirically, we focus on the roll-out of two enforcement policies over the late 2000s and early 2010s: 287(g) agreements and Secure Communities. Briefly, 287(g) agreements deputize local law enforcement agencies to enforce immigration law, and the Secure Communities (SC) program requires the fingerprints of all individuals booked in jail to be sent to U.S. Immigration and Customs Enforcement (ICE). Together, these policies were credited with more than half a million deportations and detentions over our sample period of 2005-2012. Of those detainers issued over this time period, 45% were not proceeded by a conviction, and 10% of them were due to a traffic violation (including DUI), so a broad population may have been affected by these policies.[4] Moreover, these policies are believed to have deleterious effects on immigrants who were not deported, due to fear of deportation and mistrust of local law enforcement.[5]

The empirical specification exploits both the temporal and geographic variation in the roll-out of 287(g)s and SC to examine the effects on high-skill female labor supply.[6] To conduct our analysis, we gathered data on the timing and location of the implementation of 287(g)s and SC and merged these data to the American Community Survey (ACS) from 2005-2012, which allows us to measure labor supply of high-skilled women. The smallest consistent and comprehensive geographic area available in the ACS is the Public Use Microdata Area (PUMA), so we create measures of the presence of both 287(g) agreements and SC by PUMA and year (described in more detail in Section 2). This allows us to estimate a difference-in-difference model, while controlling for PUMA and survey year fixed effects. Thus, our identification strategy relies on two key assumptions: first, there were no other time-varying differences across the PUMAs that adopted the enforcement policies compared to those that

[3]On average, college-educated households spend 30% more on household services compared to lower-education households in the Consumer Expenditure Survey: `https://www.bls.gov/cex/tables.htm#annual`.

[4]Appendix Table (A1) shows information about the criminal convictions of individuals who were detained.

[5]Wang and Kaushal (2018) show the implementation 287(g) agreements and Secure Communities increased the share of Latino immigrants with mental distress.

[6]287(g) agreements were optional and not all locations adopted them; among those that did, the timing of the adoption was not identical. While SC was not optional, it was rolled out in a staggered fashion across localities. We describe this in more detail in section 2.

did not; second, there were no time-varying differences within PUMAs that are correlated with the timing of the adoption of these policies in those PUMAs.

For our main sample–working-age (20-64) college-educated citizen women–we find strong evidence that the roll-out of these enforcement policies reduced labor supply. The estimates indicate that an increase in the intensity of immigration enforcement by any one policy (287(g) or SC) reduces the probability of working and the usual hours worked. These effects are driven by women with children, who experience a decline in work of 0.4% relative to the sample mean and in working hours by 0.18 hours per week, or 11 minutes (0.6% relative to the sample mean). This is consistent with the fact that mothers will have more household production responsibilities, and thus be more sensitive to changes in the price of outsourcing this production.

We conduct a number of additional tests to support the idea that changes in the prices of market-provided household services are driving the results. First, we examine whether the effects are bigger for women with children under 6 (before they are likely to enter school). We expect women with young children will have more household production responsibilities, and we find this group does experience larger declines in labor supply. Second, we directly test whether we can observe changes in the time spent on household production by these women with the American Time Use Survey (ATUS). The samples across the ATUS and ACS sets are not perfectly comparable, however, we find that an increase in the intensity of immigration enforcement by any one policy leads to an increase in the hours spent on household activities (e.g. cooking and cleaning) by about 1 hour per week.[7] Moreover, we see a negative and significant effect on leisure activities and no effect on time spent caring for dependents in the household (e.g. educational activities, socializing). Third, we find no significant effects on labor outcomes or time allocation for both high-skilled women without children, and high-skilled men. Fourth, we directly examine the cost of household

[7]The ATUS analysis is conducted at the county level and ATUS does not identify counties with less than 100,000 inhabitants.

production, as proxied for by wages of household workers, and we document increases in this cost in response to immigration enforcement. This effect is particularly large for female household workers, who may be more likely to be substitutes for high-skilled women in household production. Taken together, this provides strong evidence that changes in the price of outsourcing home production is an important mechanism behind the labor supply effects.

This paper builds on previous work documenting a strong positive relationship between the presence of low-skilled immigrants, and high-skilled women's labor supply in the United States (Cortes and Tessada, 2011; Furtado and Hock, 2010; Amuedo-Dorantes and Sevilla, 2014; Furtado, 2015, 2016), Italy (Peri, Romiti and Rossi, 2015; Barone and Mocetti, 2011), Hong Kong (Cortes and Pan, 2013), and Spain (Farré, González and Ortega, 2011).[8] Our paper makes several contributions to this literature. First, while the literature has focused on studying the effect of migratory inflows on the outcomes of interest, we focus on evaluating the effects of recent enforcement policies in the U.S. that focused on the removal of immigrants. 287(g)s are still in place in many areas, and President Trump has recently expanded the 287(g) program, and reinstated the SC program (Alvarez, 2017; Sakuma, 2017).[9] Therefore, understanding the spillover effects of these policies on high-skilled workers is crucially important for policy-makers as they actively change immigration policy. The second contribution is methodological: we use local enforcement policies as an exogenous driver of the size of the undocumented population, which relies on relatively innocuous and easily testable assumptions. More specifically, we conduct a number of tests to provide evidence that the results are driven by the implementation of enforcement policies. First, we show event studies to test the parallel trends assumptions and provide evidence that there were

[8]These papers primarily rely on cross-sectional variation in the concentration of immigrants across locations. With the exception of Cortes and Pan (2013), all these papers use an instrumental variables strategy in the spirit of Card (2001), which takes advantage of historical immigration settlement patterns to predict future patterns.

[9]SC was replaced by the Priority Enforcement Program in 2015, but it was reactivated in January of 2017.

no systematic differences in high-skill female labor supply before the policies were put into place across PUMAs. Second, we account for differential trends across locations in multiple ways, and our main results hold.

Our paper also contributes to several other literatures. First, a number of researchers have examined the effect of a change in the price of one specific type of household service–childcare–on women's labor supply (see for example: Baker, Gruber and Milligan (2008); Cascio (2009); Havnes and Mogstad (2011)). These papers primarily take advantage of changes in government-provided childcare, and our findings suggest that policies which affect the presence of undocumented immigrants may also be important for determining these outcomes. Second, our paper speaks to the literature on the effect of "family-friendly" policies on women's work and wages (see for example: Baker and Milligan (2008); Rossin-Slater, Ruhm and Waldfogel (2013)). Our work demonstrates that enforcement policies may have an unintended "anti-family-friendly" effect by decreasing work among women with children, which may have far-reaching consequences to the gender gap in work and wages, as well as children's well-being. We view this paper as a first step to analyzing the full impact of immigration enforcement policies on high-skilled women and their families' well-being.

The rest of the paper proceeds as follows: in the next section we provide details about the enforcement policies we focus on and the data we use. Section 3 describes our empirical strategy and section 4 presents our results. Section 5 concludes.

2 Policy Background and Data

We examine the effects of two types of local immigration enforcement policy: 287(g) agreements and the Secure Communities Program. 287(g) agreements were optional agreements law enforcement agencies could enter into with the federal government, and were authorized by the Illegal Immigration Reform and Immigrant Responsibility Act of 1996. Local and state law enforcement agencies that adopted these agreements received training from U.S. Immigration and Customs Enforcement (ICE) to carry out immigration enforcement action. In this paper we focus on the local agreements (often at the county or city level), as these have been shown to have larger effects in the corresponding local area than the state agreements (Kostandini, Mykerezi and Escalante, 2013). There were two types of 287(g) agreements over our sample period. First, the "Task Force" model, which permitted trained law enforcement officials to screen individuals regarding their immigration status during policing operations, and arrest individuals due to suspected immigration violations. Second, the "Jail" model, which allowed screening for immigration status for individuals upon being booked in state prisons or local jails.[10] By January 2011, 50 counties had either the Task Force or Jail model, and 15 had both. Figures (1) and (2) show maps of the takeup of these agreements by county. Over the 2006-2011 period, 186,089 individuals were identified for removal through the 287(g) programs.[11]

The Secure Communities program is similar to the Jail 287(g) model, but the process of screening for immigration status operated through a database, rather than trained 287(g) officers.[12] In contrast to the 287(g) agreements, the Secure Communities program was not optional and was rolled out county-by-county between 2008 and 2013 until the entire country was covered. Moreover, once SC was in place in a county, the fingerprints of all arrestees booked in jail were automatically send to ICE, who subsequently ran the fingerprints against several federal databases to determine an individuals' immigration status. The timing of county adoption was determined by the federal government and previous evidence suggests the initial set of counties was chosen based on the size of their Hispanic population and proximity to the U.S.-Mexico border, but the timing of adoption in subsequent counties was

[10]Some locations had a "Hybrid" model, which includes both the Task Force and Jail models. In our empirical specification, we do not consider a "Hybrid" model to be a separate type of policy, but instead we simply model the presence of the Jail or Task Force model separately.

[11]Removal information available here:
https://www.ice.gov/doclib/foia/reports/287g-masterstats2010oct31.pdf

[12]For a comprehensive review of the Secure Communities program's implementation see Alsan and Yang (2018), Cox and Miles (2013), and Miles and Cox (2014).

more random and based on resource constraints and waiting lists (Cox and Miles, 2013). By January of 2011, about 880 counties had SC in place, as shown in Figure (3), and over the period 2009 to 2012, 250,000 individuals were detained through SC (Miles and Cox, 2014). The other potentially important differences between the Jail 287(g) model and SC are that under SC, only ICE officers do the screening of immigration status and are allowed to initiate the removal process, whereas under the 287(g) model, the 287(g) trained officers do both.[13]

We gathered information about the implementation of these policies at the county level from a variety of sources. Start and end dates for all 287(g) agreements came from reports published by ICE, the Department of Homeland Security, the Migration Policy Institute, as well as Kostandini, Mykerezi and Escalante (2013), and various news articles. This information also allowed us to determine which type of agreement was in place–the Jail model or the Task Force model, or both. Information on the rollout dates of Secure Communities comes from ICE. Beginning in 2013 some 287(g) agreements were ended due to changes in federal rules, and SC ended in 2014. In our models we focus only on the period of program rollout–2005 to 2012–so our results should be thought of as the effect of *increasing* immigration enforcement.

We merge this information about local enforcement policies with data on local-level high-skilled citizen women's labor supply over the period 2005-2012 from the American Community Survey (ACS) (Ruggles et al., 2017). The ACS is a repeated cross-sectional dataset covering a 1% random sample of the U.S., and in the publicly available data set, the smallest geographic area available is the Public-Use Microdata Area (PUMA). PUMAs allow us to identify the location of residence for all individuals and they respect state lines. Some PUMAs are equivalent to counties, whereas others include several counties, and still others are smaller than individual counties. The policy data is at the county-level, so to merge this

[13] Additionally, funding for the 287(g) operates came partially from the local jurisdictions, whereas all SC funding came from the federal government. This program information taken from Capps et al. (2011).

with the annual PUMA-level ACS data, we calculate the population-weighted average of the county values of the enforcement variables within each PUMA, similar to the approach taken by Watson (2013).[14] Additionally, we have no information about the month of survey within the ACS, only the year of survey, so we assign to each observation the enforcement policies in January of the survey year and test the robustness of this choice. For our main analysis, we aggregate all of the polices into a summary index to maximize precision, similar to the approach taken by other researchers.[15] To do this we sum the variables indicating whether each policy was in place in a given PUMA (each ranging from 0 to 1) to create a summary measure of the number of policies in place in a given PUMA and year that takes on the value 0 to 3. In robustness checks we also explore whether there are meaningfully different effects of the three policies.

Our main sample includes citizen women ages 20-64 with a four-year college degree or more, which we refer to as "high-skilled".[16] As women with children may have more demands on household production, we also explore the results on subsamples of women with children living at home, and women with children younger than age 6 at home. The primary outcome variables in the ACS are high-skilled citizen women's usual hours per week worked in the past year. We also look at whether the woman worked any positive hours usually, and hours of weekly work conditional on positive hours. To ease computation, we collapse the ACS data to the PUMA by year level, using the ACS-provided individual sample weights, and we weight our models by the number of individuals in each cell.

Additionally, we use the data from 2005 to 2012 from the American Time Use Survey (ATUS) to examine changes over this period in women's time use beyond changes in labor

[14]If a PUMA is equivalent to a county, or smaller than a county, the PUMA will get the value of the enforcement variables for that county. If multiple counties are contained within a PUMA, we weight the value of the enforcement variable for each county by the fraction of the total PUMA population that each county represents. Additionally, the PUMA codes were revised after the 2011 ACS survey, so we use the time-consistent version of the PUMA codes provided by the IPUMS website.

[15]See for example: Amuedo-Dorantes and Lopez (2015), Bohn and Santillano (2017), and Amuedo-Dorantes, Arenas-Arroyo and Sevilla (2018).

[16]Citizens include U.S.-born as well as foreign-born who report being naturalized citizens.

supply. ATUS respondents are randomly selected from households who completed their participation in the Current Population Survey (CPS), so this is also a nationally-representative (with survey weights) cross-sectional data set.[17] We focus our analysis on measures of time spent weekly on household activities, care of household members (children and adults, separately), and leisure activities. Time on household activities include time spent on maintaining the respondent's household, like housework, cooking, and home maintenance. If, for example, the respondent's spends time on food preparation for children, this will be coded under household activities instead of childcare. Time spent caring for a household member, for example, feeding them, socializing with them and, in the case of a children, time spent on activities related to their education, are coded under care of a household member. Leisure activities include time spent socializing and on relaxation activities, sports and recreation, which may be important as an additional pathway through which women's well-being can be affected by the policies.

We construct a sample with the ATUS that is as close as possible to the sample in the ACS: citizen women aged 20-64 with a college degree or more. The main differences between the ATUS and the ACS are that the ATUS is available at the monthly and county level (rather than the annual and PUMA level) and this allows us to merge the ATUS and the enforcement data directly at both of these levels.[18] Additionally, since the sample size in the ATUS is much smaller, we run these regressions at the individual level using the ATUS-provided sample weights. Although the ATUS is nationally representative, only large counties, with population greater than 100,000 are identified, so we are not able to cover the entire U.S. with this dataset like we can with the ACS. Our results using the ATUS are therefore nationally representative only for large counties. Table (1) shows summary

[17]The ATUS interview is conducted two to five months after an individuals' last CPS interview. Interviews are conducted by phone and the interviewer collects information about the respondent's activities over a 24-hour period. We inflate this to weekly measures to match the ACS measures.

[18]We have also estimated this model using the variation of the enforcement policies at the year level based on the policy as of January, replicating the model we follow for the ACS. The results are robust to this specification.

statistics of enforcement policies for both the ACS and the ATUS. The average value of the summary index of enforcement is 0.31 in the ACS and 0.45 in the ATUS, and for both surveys SC is the most prevalent enforcement policy, followed by Jail 287(g) and finally Task Force 287(g).

Since our sample period spans the Great Recession, to account for changes in economic conditions that may influence women's labor supply, we add to the data several "Bartik-style" measures of labor demand, as well as housing price values. Details on these variables are included in the Appendix.

Summary statistics for the ACS and ATUS are in Table (1). In the ACS we have a total of 8,576 PUMA-year cells for the period between 2005 and 2012, and in the ATUS we have 6,452 individual observations for the same period. It is important to highlight that, although the women sampled in both surveys are not the same, we construct the samples to be as closely comparable as possible. The demographics of all high-skilled citizen women (column 1), high-skilled citizen women with children (column 2), high-skilled citizen women with young children (column 3), and high-skilled citizen men (column 4) across surveys show that both samples are closely related in these observable characteristics. In the ACS sample we multiply the dichotomous labor supply variables by 100 in the summary statistics and regressions, to ease presentation of the results. So, for example, 85.62% of high-skilled women worked, and this number goes down to 78.58% for women with young children. High-skilled citizen women spend on average 5.6 hours on activities related with childcare and this more than triples for women with young children, while men spend on average 2.89 hours on childcare activities. We also see the same pattern in household activities across the demographic groups.

3 Empirical Strategy

Our identification strategy exploits both the geographic and temporal variation on the implementation of enforcement policies to identify their effect on labor market outcomes of high-skilled citizen women. Our main analysis examining the effect on high-skilled women's labor supply with the ACS is estimated with the following model:

$$Y_{pt} = \alpha + \beta Enforcement_{pt} + \gamma X_{pt} + \mu_p + \delta_t + \epsilon_{pt} \tag{1}$$

Where Y_{pt} represents different measures of labor outcomes for women living in PUMA p and year t. The model also includes year fixed effects, δ_t, to account for national shocks, and fixed effects at the PUMA level μ_p to control for time-invariant unobserved heterogeneity. In addition to these variables, it is also important to control for time-variant heterogeneity both at the individual and regional level. Following Cortes and Tessada (2011), the vector of controls X_{pt} includes the average in each cell of: age and age squared, whether black, whether married, educational attainment, whether children under 6 in household, and whether any children in household.[19] It is important to include controls that account for changes in economic conditions at the PUMA level that could influence our outcomes of interest, so X_{pt} also includes Bartik-style measures of labor demand, as well as housing price values.

In our main analysis, we aggregate all of the polices into a summary index to maximize power. Thus, $Enforcement_{pt}$ ranges from 0 to 3 based on the number of enforcement policies in place, and β should be interpreted as the effect of a change in the intensity of enforcement policies by one policy.

We expect the enforcement policies will reduce high-skilled women's labor supply through increases in the cost of services that substitute for household production–such as childcare, cleaning, cooking, and gardening (Cortes and Tessada, 2011). This price increase

[19]Fertility may be directly affected by enforcement if the price of, for example child care, changes (Furtado, 2016). We directly test for this and find no evidence of changes in fertility as shown in Appendix Table (A2).

will be due to a reduction in the labor supply of undocumented individuals who provide these types of services through two channels: 1) out-migration of immigrants, and 2) reductions in immigrants' labor supply due to fear of deportation. Enforcement policies may also affect documented immigrants, if documented immigrants worry about the deportation of their friends and relatives, or fear changes in their own immigration status as a result of the policies.[20] Previous work on 287(g) agreements found these policies reduced local employment in immigrant-intensive industries (Bohn and Santillano, 2017), but the evidence is more mixed on the effect on migration of immigrants, with some studies finding little to no effects (Watson, 2013), and some studies finding suggestive evidence of out-migration (Capps et al., 2011).[21] Research on Secure Communities is more limited, however East et al. (2018) find a negative effect of SC on the employment of low-skilled male immigrants, and evidence of negative spillover effects on the employment of male citizens working in middle to high-skill occupations.

Our identification strategy relies on two key assumptions. First, there are no other time-varying differences across the PUMAs that adopted the enforcement policies compared to those that did not; and, second, there are no time-varying differences within PUMAs that are correlated with the timing of the adoption of these policies in those PUMAs. We directly test the assumption of parallel pre-trends before policy implementation. Figure (4) shows the effect of enforcement on high-skilled women's labor outcomes before and after the implementation of the enforcement policies. As there are three enforcement policies, here we only use the first policy passed in each PUMA to define "event time", so the "post" period may include passage of other enforcement policies, but the "pre" period only includes years

[20] Alsan and Yang (2018) finds a negative effect of exposure to SC on sign-ups for the Affordable Care Act (ACA) and Supplemental Nutrition Assistance Program (SNAP) participation for Hispanic citizens. These results suggest enforcement policies can affect both the undocumented and documented immigrant population.

[21] Watson (2013) examines the effect of enforcement policies on immigrant's location choice. She finds that although enforcement policies do not cause immigrants to leave the United States, they do increase migration to a new region within the United States. However, these effects are concentrated in Maricopa County, AZ and among high-skilled foreign-born, who are unlikely to be undocumented.

with no enforcement policies. We show three different event studies depending on which policy was implemented first. The blue line shows the effect of the enforcement policy, and the 95% confidence intervals are shown by the dashed black lines. Year 0 on the horizontal axis represents the year in which the first enforcement policy was implemented, and the effects on the outcomes of interest and are expressed relative to Year -1. The PUMAs with no enforcement policies in our sample period are used to identify the year fixed effects. The three different graphs for each policy show the effect on each of our main outcomes of interest: whether worked, usual hours worked, and usual hours worked condition on working (from left to right). The figures show no consistent evidence that the outcomes of interest were following a differential trend across locations prior to the adoption of enforcement policies, and they also suggest that the enforcement policies–particularly Jail 287(g) and SC–reduced the labor supply of high-skilled women. However, due to large confidence intervals, which partly motive our choice to use a summary index, we unable to draw strong conclusions from these figures.

Additionally, our estimates may be biased if there is selected migration of high-skilled women: for example, if high-skilled women move away from counties with a less friendly environment towards migrants. We estimate the effect of enforcement on migratory responses of both citizens and non-citizens and find no evidence of changes in migration, discussed in more detail below. It is important to note that any migration of low-skilled immigrants in response to the policy is part of the mechanism with which these policies affect high-skilled women's outcomes, so we do not view migration of low-skilled immigrants as biasing our estimates.

4 Results

We begin our analysis by showing the effects of enforcement policies on the labor supply of all high-skilled citizen women, as well as women with children, and women with young children in Table (2). The model, based on equation (1), includes all demographic and economic controls described in the previous section. The results show a significant effect of enforcement policies on the labor supply of high-skilled women. The results in Panel A for the full sample show that an increase in the intensity of enforcement by one policy reduces the probability of working by 0.19 percentage points, which is a reduction of working at all of 0.23% relative to the sample mean (p=0.05). The results in column (2) show that these women also decrease the hours worked per week by 0.13 hours or about 8 minutes (0.38% relative to the sample mean, p=0.02). In column (3) we look at hours worked conditional on working and also see a marginally significant decline of 0.14% (p=.10) though this may be driven by changes in the composition of workers. Estimates for women with children are larger than the full sample (Panel B), and for women with young children the effects even larger (Panel C), as predicted. For women with children of any age, the reduction in the likelihood of working is about 0.36%, and for the sample of women with young children the reduction is about 0.88%. The point estimate on working hours is also bigger for mothers. Since the average hours of work is lower for mothers, this represents an effect in percentage terms that is much larger than the full sample–e.g., a reduction in hours of 1.26% for mothers of young kids.

Because outsourcing of household production may be important for women who work longer hours, we also examine whether the enforcement policies affect the propensity to work more than 50 and 60 hours per week in Appendix Table (A3). Overall the effects are negative although imprecisely estimated and not statistically different from zero. However, focusing only on these point estimates, the effect sizes are large: there is a reduction in the likelihood of working 50 or more hours per week of 0.1 percentage points, or 0.6%, and a reduction in 60 or more hours per week of 0.1 percentage points, or 2% for the full sample. This is indicative that these enforcement policies may be particularly impactful for women working long hours, and may have important implications for the potential career progression of women in very time-intensive jobs (Bertrand, Goldin and Katz, 2010).

4.1 Mechanisms

To explore in more detail how women's time allocation is changing we estimate the following empirical model with the ATUS data:

$$Y_{icmt} = \alpha + \beta_2 Enforcement_{icmt} + \gamma X_{icmt} + \lambda_m + \mu_c + \delta_t + \epsilon_{icmt} \tag{2}$$

All the control variables are the same as in equation (1) except they are for the individual, not the average PUMA-year cell, and, in addition to the previous controls, we also add month fixed effects and a dummy for whether the time-use data was collected for a weekday or a weekend day. Y_{icmt} measures the time (hours per week) allocated to care of household members (children and adults), household activities and leisure activities.

Table (3) shows the effect of enforcement policies on the number of hours per week spent in activities related to household care of children and adults (columns (1) and (2)), household activities (column (3)) and leisure activities (column (4)). Estimating the effect of the policies on care of household members and household activities separately is important because it sheds light on the different types of activities performed at home for which a woman is likely to hire services. Recall that activities like feeding and socializing with children are included in care of household members, but activities like preparing food for children are included in household activities.

The results in Panel A of Table (3) for the full sample of high-skilled women show no significant effects on time spent on care of household members, but an increase of about an hour per week on household activities when the intensity of enforcement increases by one policy (p<0.10). This indicates that time actively interacting with children is not changed, but that time spent on household chores (such as preparing meals) is affected. These results are consistent with Amuedo-Dorantes and Sevilla (2014) who find the presence of low-skilled immigrants decreases the time spent on basic childcare, but it does not affect time spent on educational activities.[22] Along the lines of the findings in Table (2), when restricting the sample to mothers (Panel B), we see stronger effects. Mothers increase the time spent on household activities by 1.2 hours (p<0.10), and there is a reduction of about 1.3 hours per week on leisure activities (p<0.05). This is an additional way in which women's well-being could be indirectly affected by the implementation of enforcement policies. For high-skilled women with young children (Panel C) we see similar declines as for the full sample of mothers, although the standard errors are much larger likely due to the much smaller sample size (N=1610). Interestingly, the effect on care of children does become more negative on this subgroup, although there are very large confidence intervals.

When interpreting the results from the ATUS sample, it is important to keep in mind the differences in the sample between the ATUS and ACS–in particular, we can only observe individuals living in large counties in the ATUS. To make a more direct comparison between these two data sets, we re-estimate our ACS models using only women in the counties that we can observe in the ATUS. These results are shown in Table (A4) for mothers only. Estimating the models at the PUMA-level but keeping on counties observable in the ATUS (Panels B and E) causes the main estimates to shrink slightly and the standard errors to rise, so that the point estimates are no longer statistically different from zero. Additionally, the sign on the estimated effect on work >0 hours for mothers of young kids flips. Estimating the models at the county-level with the same observations yields largely similar results. This suggests that the pattern of results is broadly consistent across the data sets, however some

[22]Specifically, Amuedo-Dorantes and Sevilla (2014) find the 2 percentage point increase in the share of low-skilled immigrants from the 1970s to 2000s reduced time spent in basic childcare by about 30 minutes per week, and increased the time spent in educational activities by about 15 minutes per week.

caution should be exercised in direct comparisons between the point estimates in the ACS main analysis and the ATUS main analysis.

As additional evidence of changes in the cost of outsourcing household production, we test the effect of the enforcement policies on the wages of household workers. We examine the effects for all workers and across the wage distribution (in increments of 10 percentiles starting from the 5th percentile to the 95th percentile) for female and male household workers, shown in Figure (5).[23] Our findings indicate increases in the log weekly wages of both female and male household workers. Overall, we find a statistically insignificant increase in wages for males of 0.5% and a statistically significant increase of 2% for females. Moreover, this increase is larger in the lower part of the wage distribution, where undocumented immigrants are most likely to be.[24] The point estimates indicate, for example, a marginally significant 2% increase in wages in the 20th percentile for women in response to one additional enforcement policy, and an insignificant 0.003% decline in the 85th percentile. This provides further evidence that this is an important mechanism through which enforcement affects high-skilled citizen women. As points of comparison, Furtado (2016) finds that a 1% change in the low-skilled immigrant population in the U.S. reduced the median wage of child care workers by about 4%, and Cortes (2008) finds that a 10% increase in low-skilled immigrants reduced the price of immigrant-intensive services (mostly household services) by roughly 2%. To compare this to the potential effect of enforcement policies, we note that 1% of the low-skilled immigrant population today is roughly 225,000 individuals and over our sample period about 450,000 individuals were directly affected by these enforcement policies through detention (see section 2).

[23]For this analysis we use the ACS and look at a sample of working-age adults (20-64) who report either their industry or occupation of work is household services.

[24]Appendix Figure (6) plots the share of workers by wage percentile bin that are non-citizens, low-skilled non-citizens, and by gender. The left-hand-side dot represents workers in the 0-5th percentile of the wage distribution and so on. Note that one possibility is that enforcement policy induces workers to switch from formal work to more informal work, which might include household services. However, these results show the net effect on all workers who report household services as their industry or occupation, so this switching should be included in this total result.

4.2 Effects on Low-Impact Groups

The results so far suggest a change in household production is an important mechanism through which enforcement policies affect high-skilled women's labor supply. However, there are other channels through which changes in the labor supply of undocumented immigrants could affect high-skilled individuals' work, such as complementarities in the production process of market work (Chassamboulli and Peri, 2015). We therefore look at the effect of enforcement on two different groups in the population whose labor supply should not be as highly affected through changes in the price of outsourcing household production. First, we look at high-skilled men. We argue that since women have been found to be more sensitive to changes in the price of household services in other contexts (such as child care), and because women spend more time in household production (20 vs. 12 hours in our sample), high-skilled men are less likely to change their time use directly due to the changes in the cost of household services. Second, we estimate the effects for high-skilled women with no children. The presence of a child at home affects the demand of household services, and when these services become more expensive, the family might need to adjust their time use to take care of children. Table (4) and Table (5) show the results for these two groups for labor outcomes and time allocation, respectively. The results show small and insignificant effects both for high-skilled men and high-skilled women without children. Although the sign of the coefficients in Table (4) goes in the same direction of those in Table (2), their magnitudes are smaller both in absolute levels and in percentage terms, and the results in Table (5) for high-killed men show coefficients in the opposite direction to those found for the main sample of women. These results further suggest that the effects we find for high-skilled women are at least in part, and may be fully, operating through the mechanism of reduced prices of household services. Due to these smaller and statistically insignificant findings for high-skilled women we focus only on mothers for the remainder of the analysis.

4.3 Effects by Policy

As discussed previously, the three policies are similar in design, but they do have some potentially important differences. We directly investigate whether the roll-out of the three policies had similar effects in Tables (6) and (7) for all mothers and mothers of young children, respectively. We first include each policy in a separate regression one at time in columns (1)-(3). We then estimate a model where all the policies are included at the same time in column (4), and finally we estimate a model with our baseline summary index that assumes a linear and additive effect of these policies in column (5).

The point estimates in columns (1)-(3) show that the Jail 287(g) agreements and SC have similarly large effects, although not always statistically significant. The Task Force effects are less consistent. These results largely follow what was shown in the event study graphs in Figure (4). When we include all three policies in the same model, in column (4), the pattern is similar. The p-values shown at the bottom of each panel indicate that we cannot reject the effects of Jail 287(g) and SC are the same, and that together all three are highly jointly statistically significant for all outcomes we found statistically significant effects for using the baseline summary index (shown in column (5)). Moreover, we cannot reject the three policies are the same when looking at usual hours worked per week conditional on working in Panel C (however Task Force 287(g) agreements are statistically different than the other policies in Panels A and B). These results broadly support the assumptions underlying the summary index as a measure of enforcement intensity.

4.4 Robustness Checks

We test the robustness of our results next. First, we test the sensitivity of the findings to alternative timing assumptions. In the baseline results, we code an enforcement policy as being in place in a given survey year if it was in place in January of that year. Since the ACS interviews are conducted continuously throughout the year, but we do not know the month of the interview, we test the sensitivity of the findings to alternative timing assumptions. Appendix Table (A5) Panel A replicates the results from the main specification that uses enforcement in January to code the summary index; in Panel B we show the results coding the enforcement policy as the fraction of the current survey year; and, Panel C shows the fraction of the year before the survey each policy was in place. The results are very similar across all specifications, indicating our modeling choice does not affect the results.

Second, in order for the difference-in-differences model to be valid, there should not exist time-varying differences across the PUMAs that adopted enforcement policies compared to those that did not. The event studies provide evidence suggesting there were no systematic differences in high-skilled female labor supply before the policies were put into place across PUMAs. In addition, we consider here including PUMA-specific time trends to control for linear differences in the evolution of the outcomes. We conduct two additional empirical tests showed in Table (8) to show the validity of our empirical specification. Recent studies discuss the challenge associated with separating out pre-trends from the dynamic effects of a policy shock when using a difference-in-difference approach (Wolfers, 2006; Lee and Saez, 2012; Meer and West, 2016). In our case, PUMA-specific linear trends would attenuate the estimated effect of enforcement policies if these affect the *growth* of labor and time allocation outcomes of high-skilled women, rather than their *levels*. Given that the event study plots suggest there may be dynamic treatment effects, we follow two alternative strategies to control for pre-trends without the risk of attenuation-bias. First, we include interactions of PUMA pre-treatment characteristics with time trends following Hoynes and Schanzenbach (2009) and Almond, Hoynes and Schanzenbach (2011). In order to account for pre-treatment characteristics we interact changes between 2000 and 2005 in 16 PUMA characteristics with time trends.[25] Panels A and D replicate the results for women with children and young

[25]The variables included are labor force participation rate, share of citizens, blacks, non-citizens, individuals with children and young children, individuals working more than 50 and 60 hours, total people and women with a college degree, masters degree, and a Ph.D. The results in Table (8) show the estimations

children, respectively, from Table (2), and Panels B and E show the results for these two samples, when adding pre-treatment characteristics interacted with a time trend. The results show that the negative effects of enforcement policies on women's labor supply persist when using this alternative specification. Second, we identify PUMA-specific time trends only from the pre-treatment time periods, and then we extrapolate these trends for the entire sample period (Wolfers, 2006; Lee and Solon, 2011; Goodman-Bacon, 2016; Borusyak and Jaravel, 2017). Panels C and F show this with all PUMAs, where a trend is estimated for never adopters without extrapolation. These results are broadly consistent with the baseline except with larger standard errors so that the estimates are no longer significant. However, we note that confidence intervals overlap with the confidence intervals on the baseline specification.

Third, motivated by similar concerns, we test the robustness of the results to dropping areas that adopted SC in 2008-2009, as these may be more highly selected. The results, in Appendix Table (A6) are very similar to the full sample. Next, since housing prices may be directly affected by immigration enforcement, we include more aggregate measures of housing prices instead in Appendix Table (A7). The results are similar with state-level housing prices, or state-level housing prices that leave out each individual PUMA.

Finally, if high-skilled citizens or low-skilled immigrants migrate as a response to enforcement policies, our estimates could be biased. Table (A8) shows the results of a model that estimates the effects of enforcement policies on the migration rates of high-skilled citizen mothers in columns (1) and (2). We also look at the migration rates of low-skilled non-citizen women and men workers, who may be directly affected by enforcement, in columns (3) and (4), and non-citizen women and men household workers in columns (5) and (6). To estimate this model we exploit information from the ACS about place of residence last year.[26] The

when using the change in these variables between 2000 and 2005 interacted with a time trend, but the results are robust to using only the levels in 2000 or in 2005 interacted with a time trend.

[26]The ACS provides information on place of residence at the MIGPUMA level (slightly larger than the PUMA level in our main analysis), which identifies the place of residence the year prior to the interview.

migration rate for each group is defined as the number of migrants in a given demographic group per 100,000 people relative to the population in 2005. The results in Table (A8) show that the implementation of the enforcement policies did not have a significant effect on the migration rates of any of the population groups of interest. This suggests that migration is not the driver of the effects found in the main analysis for high-skilled women. This also suggests that *within* U.S. migration is not a driven of the response of immigrants, although this does rule out changes in migration to and from the U.S., which is not measured here.

4.5 Discussion

Low-skilled immigrants are over-represented in household services, and a policy-driven decrease in immigration may result in an increase in the price of these services, which has important consequences for workers who outsource household production. Our results support this hypothesis; they indicate a statistically significant effect of the roll-out of enforcement policies on high-skilled mother's labor supply. When interpreting our results, it is important to remember that our estimates are the "Intent to Treat" effect of the policy and the effects among mothers who change their outsourcing of household production may be much larger. Comparing our estimates to those in the related literature is difficult, as other papers typically look at how high-skill women's labor supply is related to the quantity of immigrants in a local area. For example, Cortes and Tessada (2011), which use the closest sample to ours, but take a different approach to identification, find that a 10% increase in low-skill immigration in the U.S. was associated with an increase in hours of work by 0.3% among women earning wages at the top of the distribution. Our main estimates on working women (who would have an observable wage and would thus be in the Cortes and Tessada (2011) sample) are similar–about a .5% decline–however, this result has a wide confidence interval. Coupling this with the findings in Cortes (2008)–that a 10% increase in low-skill immigration

We generate migration rates at the consistent MIGPUMA level using this information.

decreased prices of immigrant-intensive services of 2%, which is in the same range as our estimated effect on household worker wages–our results suggest similar elasticity of female labor supply to the price of household services. In particular, our estimates indicate an elasticity of about -0.25, assuming that the entire change in high-skilled women's labor supply is due to changes in the wages of household workers.

In a different context, Farré, González and Ortega (2011) find that, in Spain, a 10 percentage point increase in the predicted number of female immigrants living in a local area increases the likelihood women with children or elderly dependents living with them work by about 2 percentage points. In the paper using the empirical approach most similar to ours, but in a very different setting, Cortes and Pan (2013) examine the effect of a series of policy changes in the 1970s to 2000s regarding foreign domestic workers in Hong Kong on high-skill women's labor supply. To identify the effects of these policy changes, they compare long-run changes in the labor supply of women with and without children over the period of these policy changes in Hong Kong. [27] They find that women with young children increase the likelihood of working by 12-13 percentage points over time.

5 Conclusion

This paper examines the effect of a recent surge in local interior immigration enforcement on high-skilled women's labor supply. We find that an increase in the intensity of immigration enforcement reduces the labor supply of high-skilled citizen mothers. To provide support for the hypothesis that changes in the price of outsourcing household services are the primary mechanism behind the labor supply results, we also look at the hours spent in household production of these women, as well as the labor supply responses of groups in the population

[27] Cortes and Pan also have a third difference and compare these changes in Hong Kong to similar changes over the period in Taiwan, as well as estimate a structural model, which yields similar results as in their quasi-experimental method.

who are less likely to be affected by a change in these prices, and finally we directly examine changes in the wages of household workers. All of these results suggest that this is an important mechanism. Importantly, the time use results indicate that the decrease in labor supply was accompanied by an increase in time spent in household production and a decrease in leisure time, but no effects on time spent caring for dependents in the household. This has important implications for both women's well-being, as well as that of their children.

We test the assumptions of our empirical specification by verifying parallel pre-trends in an event study approach. Moreover, we examine whether the effects differ across policies and find little consistent evidence that they do. Our results are also robust to a variety of alternative modeling choices including alternative controls for trends, housing prices, and timing of the policies.

The results of this paper show important spillover effect of immigration enforcement policies aimed to affect only the migrant population. These spillover effects are particularly important to quantify today, as immigration policy, specifically increased interior enforcement, is being actively debated and changed.

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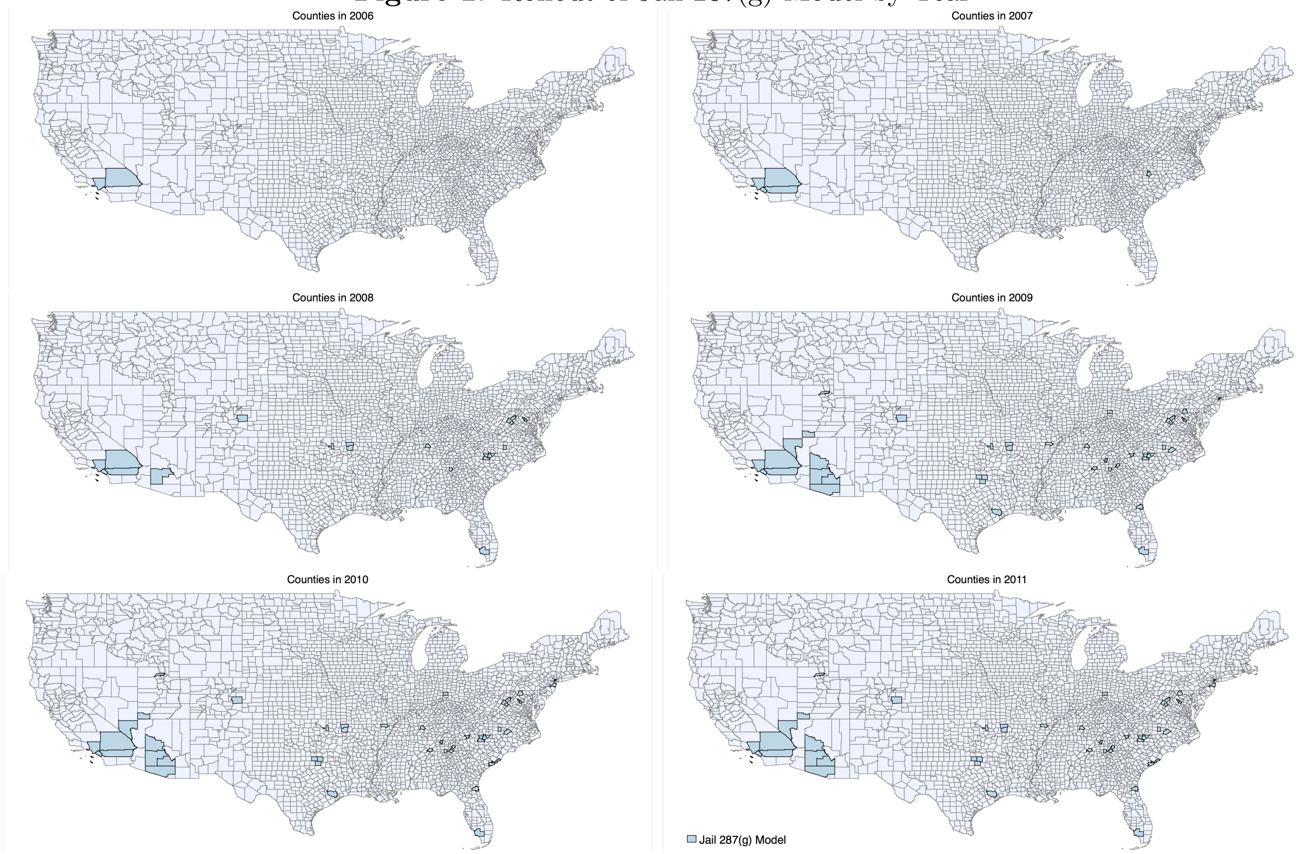
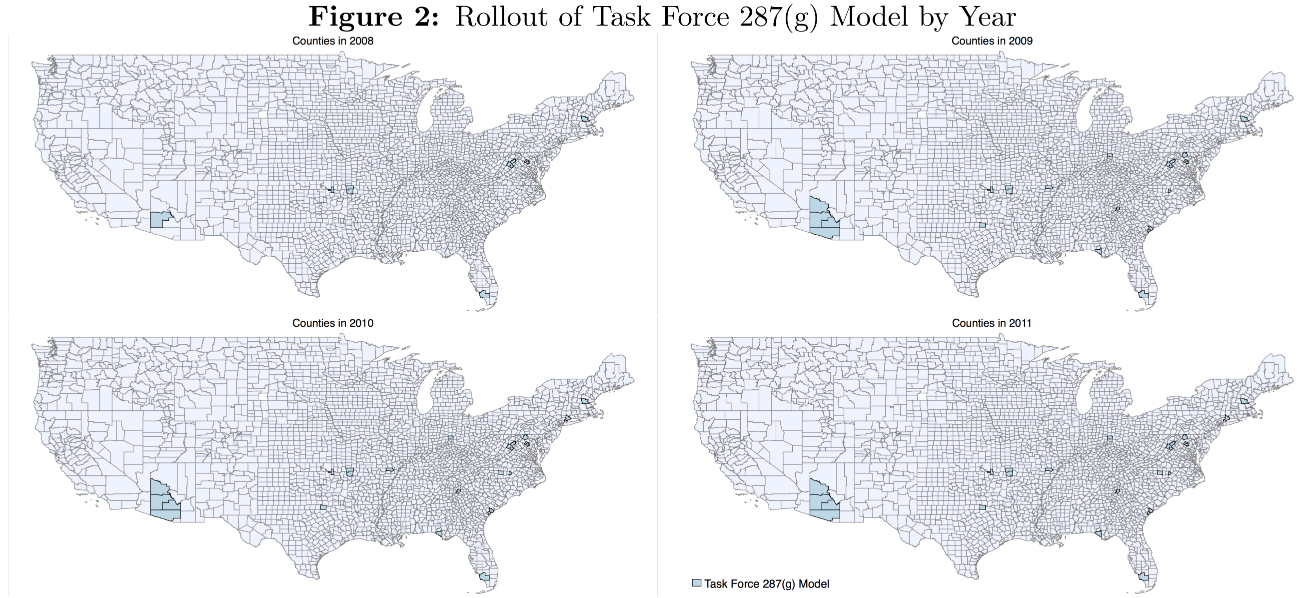
6 Figures

Figure 1: Rollout of Jail 287(g) Model by Year



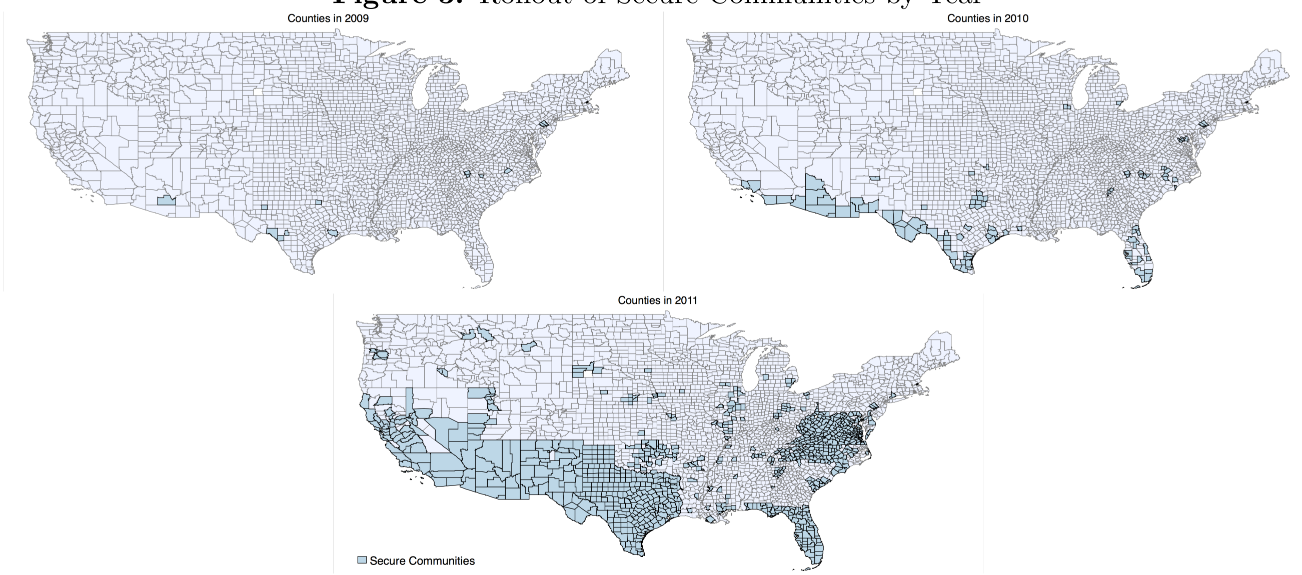
Notes: Counties with a Jail 287(g) agreement based on January of each year are shaded. See text for sources.

Figure 2: Rollout of Task Force 287(g) Model by Year



Notes: Counties with a Task Force 287(g) agreement based on January of each year are shaded. See text for sources.

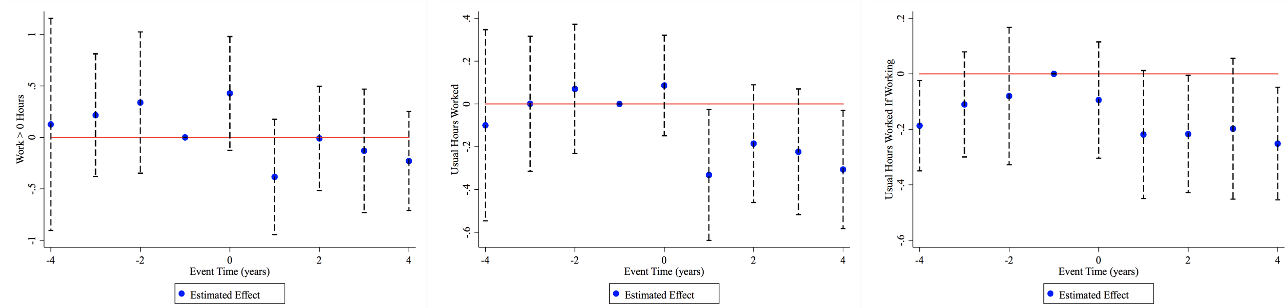
Figure 3: Rollout of Secure Communities by Year



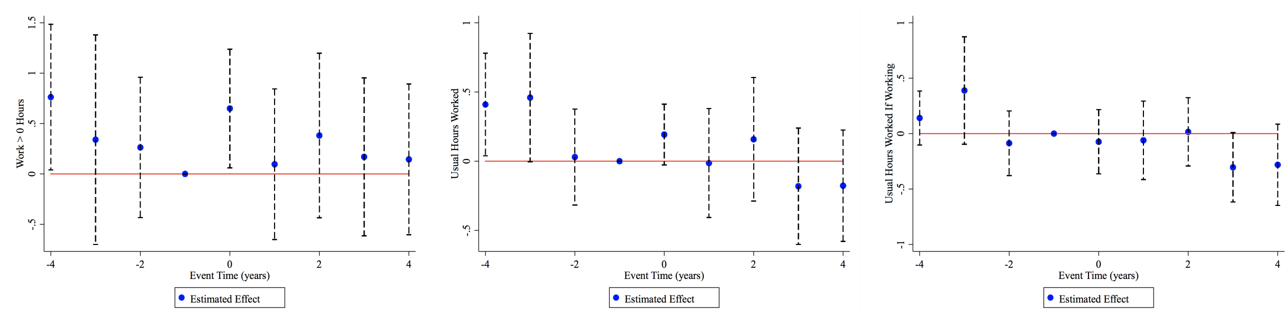
Notes: Counties that had adopted the Secure Communities based on January of each year are shaded. See text for sources.

Figure 4: Effect of Enforcement on High Skill Women's Labor Supply

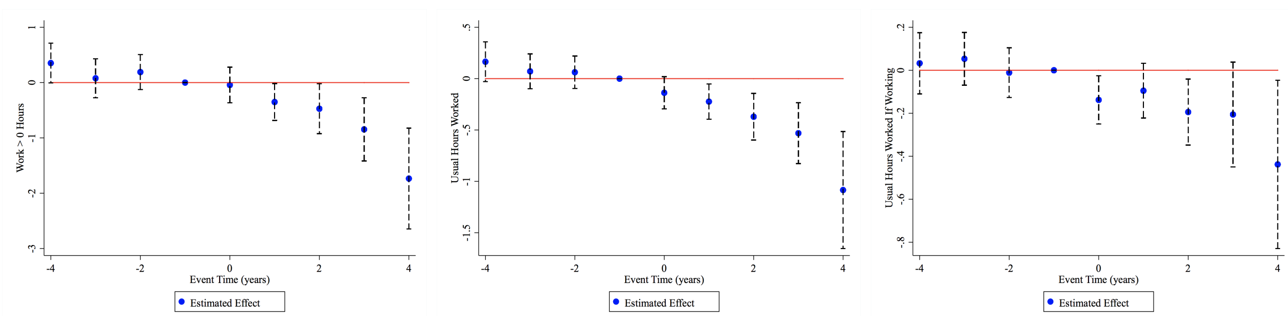
(a) First Policy is Jail 287g



(b) First Policy is Task 287g

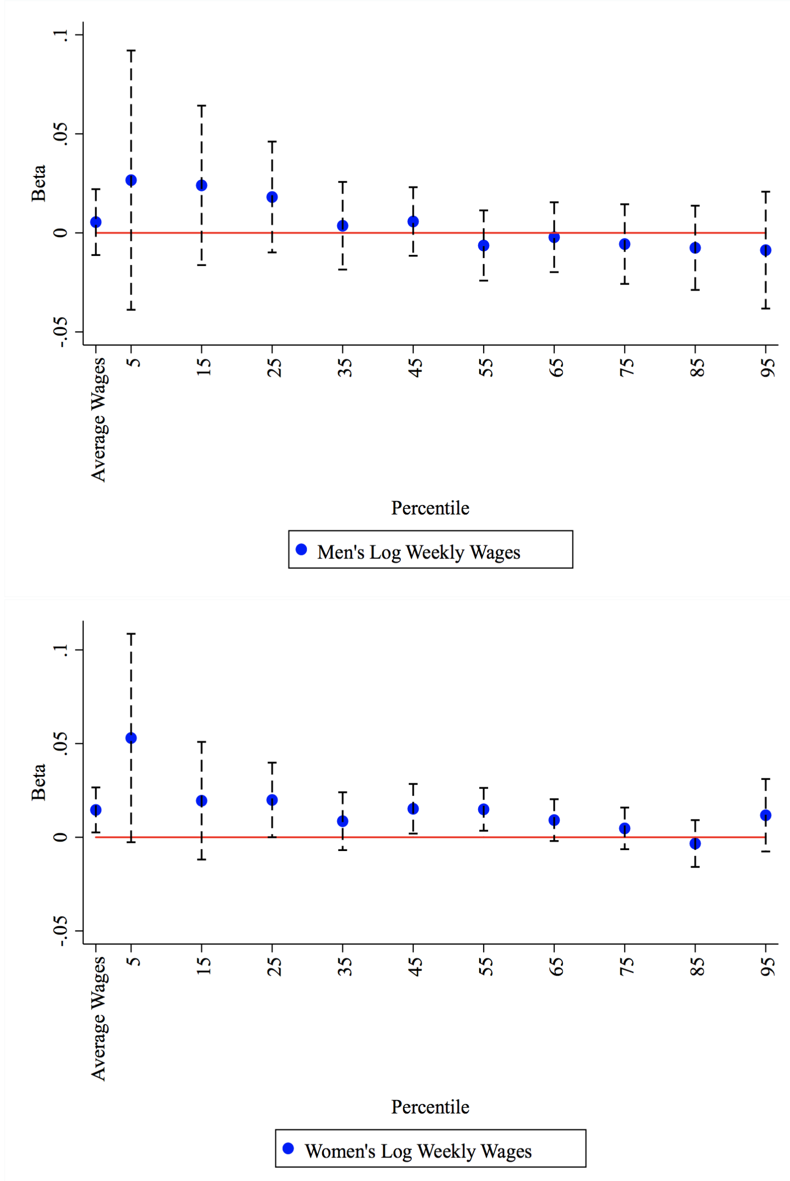


(c) First Policy is SC



Notes: Data are from the 2005-2012 American Community Survey. The sample includes all U.S. citizen women with a college degree or more ages 20-64 and the data is collapsed at the PUMA by year level. The model includes PUMA-level demographics, PUMA fixed effects, and year fixed effects. Additionally, we include demographic controls based on the cell-level averages of age, number of kids, number of kids under age 6, educational attainment, marital status, and race. We also include labor demand controls, and housing price controls at the PUMA level. Standard errors are clustered at the PUMA level and the 95% confidence intervals are shown by the dashed lines. The results are weighted using the number of women in each PUMA by year cell. The horizontal axis denotes "event time" where the omitted year is the year before the first policy (of each type) was implemented.

Figure 5: Effect of Enforcement on All Household Worker's Log Wages By Percentile



Notes: Data are from the 2005-2012 American Community Survey. The sample includes all individuals aged 20-64 who report working in the household service industry or occupation and the data is collapsed at the PUMA by year by gender level. The model includes PUMA-level demographics, PUMA fixed effects, and year fixed effects. Additionally, we include demographic controls based on the cell-level averages of age, number of kids, number of kids under age 6, educational attainment, marital status, and race. We also include labor demand controls, and housing price controls at the PUMA level. Standard errors are clustered at the PUMA level and the 95% confidence intervals are shown by the dashed lines. The results are weighted using the number of workers in each cell. The horizontal axis denotes the percentile at which the effect on wages are evaluated. The far left-and-side estimate is for average wages across all percentiles. Effect on average male household worker wages is 0.005 with a standard error of 0.008, shown in the left-hand-side bar. Effect on average female household worker wages is 0.015 with a standard error of 0.006, shown in the left-hand-side bar. Effect on overall household worker wages is 0.012 with a standard error of 0.005 (estimate not shown in figures).

7 Tables

Table 1: Summary Statistics

	High-Skilled Women			High-Skilled Men
	All	With Kids	With Kids Under 6	All
ACS				
Demographics				
Age	41.85	41.96	34.29	43.38
Black	0.09	0.09	0.08	0.06
Married	0.61	0.82	0.89	0.66
# Children Under 6	0.20	0.43	1.30	0.20
# All Children	0.86	1.83	1.94	0.84
College Degree	0.67	0.67	0.66	0.66
Masters Degree	0.26	0.26	0.25	0.22
Ph.D.	0.08	0.08	0.08	0.12
Labor Supply Variables				
Work >0 Hours (*100)	85.62	82.88	78.58	93.14
Usual Hours Worked	33.10	30.97	28.46	41.43
Usual Hours Worked if Working	38.69	37.33	36.17	44.47
Enforcement Variables				
Jail 287(g)	0.09	0.09	0.08	0.09
Task 287(g)	0.03	0.03	0.03	0.03
SC	0.19	0.19	0.18	0.19
Summary Index	0.31	0.30	0.29	0.31
N	8576	8576	8572	8576
ATUS				
Demographics				
Age	41.61	39.92	35.15	42.83
Black	0.10	0.08	0.07	0.07
Married	0.63	0.86	0.90	0.47
# Children Under 6	0.23	0.55	1.15	0.22
# All Children	0.91	1.99	1.94	0.90
College Degree	0.66	0.67	0.64	0.66
Masters Degree	0.31	0.31	0.33	0.29
Ph.D.	0.03	0.03	0.03	0.05
Time Use Variables				
Care Children in Household	5.61	13.60	19.81	2.89
Care Adults in Household	0.17	0.11	0.12	0.14
Household Activities	13.79	14.80	15.14	9.06
Leisure Activities	25.86	16.38	21.01	29.08
Enforcement Variables				
Jail 287(g)	0.12	0.12	0.13	0.13
Task 287(g)	0.04	0.04	0.05	0.04
SC	0.28	0.28	0.28	0.29
Summary Index	0.45	0.45	0.45	0.46
N	6452	3479	1667	5415

Notes: Data are from the 2005-2012 American Community Survey and the American Time Use Survey. The sample includes all U.S. citizens with a college degree or more, ages 20-64. The results are weighted using the number of individuals in each PUMA by year cell in the ACS, and by individual-level weights in the ATUS.

Table 2: Effect of Enforcement on High-Skilled Women's Labor Supply by Presence of Children

	Work > 0 Hours	Usual Hours Worked	Usual Hours Worked If Working
A: Full Sample			
Summary Index	-0.194**	-0.125**	-0.054
	(0.098)	(0.053)	(0.033)
Mean Y	85.52	33.10	38.69
P-Value	0.05	0.02	0.10
N	8576	8576	8576
B: Kids of Any Age			
Summary Index	-0.314**	-0.180***	-0.079
	(0.134)	(0.068)	(0.051)
Mean Y	82.88	30.97	37.33
P-Value	0.02	0.01	0.12
N	8576	8576	8576
C: Kids Under 6			
Summary Index	-0.643**	-0.344***	-0.118
	(0.263)	(0.118)	(0.090)
Mean Y	78.58	28.47	36.17
P-Value	0.01	0.00	0.19
N	8572	8572	8565

Notes: Data are from the 2005-2012 American Community Survey. The sample includes all U.S. citizen women with a college degree or more ages 20-64 and the data is collapsed at the PUMA by year level. The model includes PUMA-level demographics, PUMA fixed effects, and year fixed effects. Additionally, we include demographic controls based on the cell-level averages of age, number of kids, number of kids under age 6, educational attainment, marital status, and race. We also include labor demand controls, and housing price controls at the PUMA level. The results are weighted using the number of women in each PUMA by year cell. Standard errors clustered at the PUMA level. * p<0.10, ** p<0.05, *** p<0.01

Table 3: Effect of Enforcement Time Use on High-Skilled Women by Presence of Children

	Care HH Children	Care HH Adults	Household Activities	Leisure Activities
A: Full Sample				
Summary Index	0.017	0.146	0.957*	-1.266
	(0.247)	(0.099)	(0.532)	(0.780)
Mean Y	5.61	0.17	13.80	25.86
N	6443	6443	6443	6443
B: Kids of Any Age				
Summary Index	-0.017	0.029	1.248*	-2.025**
	(0.604)	(0.063)	(0.687)	(1.013)
Mean Y	13.61	0.11	16.19	22.05
N	3455	3455	3455	3455
C: Kids Under 6				
Summary Index	-0.255	0.156	1.193	-1.403
	(1.098)	(0.129)	(0.978)	(1.238)
Mean Y	19.85	0.12	15.08	21.05
N	1610	1610	1610	1610

Notes: Data are from the 2005-2012 American Time Use Survey. The sample includes all U.S. citizen women with a college degree or more ages 20-64. The model include county fixed effects, year fixed effects, month fixed effects, and whether the interview was conducted during the weekend. Additionally, we include demographic controls of age, number of kids, number of kids under age 6, educational attainment, marital status, and race. We also include labor demand controls, and housing price controls at the county level. The results are weighted using the ATUS person weights. Standard errors clustered at the county level. * p<0.10, ** p<0.05, *** p<0.01

Table 4: Effect of Enforcement on Labor Supply of Low Impact Population Groups

	Work > 0 Hours	Usual Hours Worked	Usual Hours Worked If Working
A: High-Skilled Men			
Summary Index	-0.093	-0.063	-0.023
	(0.070)	(0.042)	(0.032)
Mean Y	93.14	41.44	44.47
N	8576	8576	8576
B: High-Skilled Women with No Children			
Summary Index	-0.058	-0.054	-0.030
	(0.117)	(0.068)	(0.043)
Mean Y	87.83	34.97	39.79
N	8576	8576	8576

Notes: Data are from the 2005-2012 American Community Survey. The sample includes U.S. citizen men and women with a college degree or more ages 20-64 and the data is collapsed at the PUMA by year level. The model includes PUMA-level demographics, PUMA fixed effects, and year fixed effects. Additionally, we include demographic controls based on the cell-level averages of age, number of kids, number of kids under age 6, educational attainment, marital status, and race. We also include labor demand controls, and housing price controls at the PUMA level. The results are weighted using the number of women in each PUMA by year cell. Standard errors clustered at the PUMA level. * p<0.10, ** p<0.05, *** p<0.01

Table 5: Effect of Enforcement on Time Use of Low Impact Population Groups

	Care HH Children	Care HH Adults	Household Activities	Leisure Activities
A: High-Skilled Men				
Summary Index	-0.327	-0.026	-0.834	0.569
	(0.269)	(0.056)	(0.606)	(1.041)
Mean Y	2.89	0.14	9.06	29.05
N	5397	5397	5397	5397
B: High-Skilled Women with No Children				
Summary Index	-0.015	0.252	0.643	-0.989
	(0.059)	(0.175)	(0.801)	(1.183)
Mean Y	0.09	0.22	12.12	28.43
N	2936	2936	2936	2936

Notes: Data are from the 2005-2012 American Time Use Survey. The sample includes U.S. citizen men and women with a college degree or more ages 20-64. The model include county fixed effects, year fixed effects, month fixed effects, and whether the interview was conducted during the weekend. Additionally, we include demographic controls of age, number of kids, number of kids under age 6, educational attainment, marital status, and race. We also include labor demand controls, and housing price controls at the county level. The results are weighted using the ATUS person weights. Standard errors clustered at the county level. * p<0.10, ** p<0.05, *** p<0.01

Table 6: Effect of Enforcement Policies Separately on High Skill Women's Labor Supply, Women with Kids of Any Age

	(1)	(2)	(3)	(4)	(5)
A: Work > 0 Hours					
Jail 287(g)	-0.437			-0.420	
	(0.287)			(0.289)	
Task 287(g)		0.179		0.500	
		(0.361)		(0.392)	
Secure Communities			-0.497**	-0.477**	
			(0.196)	(0.199)	
Summary Index					-0.314**
					(0.134)
Mean Y	82.88	82.88	82.88	82.88	82.88
P Jail=Task				0.10	
P Jail=SC				0.88	
P SC=Task				0.03	
F Joint Sig				0.03	
N	8576	8576	8576	8576	8576
B: Usual Hours Worked					
Jail 287(g)	-0.291**			-0.277**	
	(0.132)			(0.139)	
Task 287(g)		0.029		0.221	
		(0.216)		(0.240)	
Secure Communities			-0.255**	-0.237**	
			(0.101)	(0.103)	
Summary Index					-0.180***
					(0.068)
Mean Y	30.97	30.97	30.97	30.97	30.97
P Jail=Task				0.11	
P Jail=SC				0.83	
P SC=Task				0.09	
F Joint Sig				0.01	
N	8576	8576	8576	8576	8576
C: Usual Hours Worked If Working					
Jail 287(g)	-0.168			-0.155	
	(0.114)			(0.122)	
Task 287(g)		-0.075		0.015	
		(0.185)		(0.202)	
Secure Communities			-0.080	-0.065	
			(0.075)	(0.077)	
Summary Index					-0.079
					(0.051)
Mean Y	37.33	37.33	37.33	37.33	37.33
P Jail=Task				0.52	
P Jail=SC				0.56	
P SC=Task				0.72	
F Joint Sig				0.42	
N	8576	8576	8576	8576	8576

Notes: Data are from the 2005-2012 American Community Survey. The sample includes all U.S.-born women with a college degree or more ages 20-64 and the data is collapsed at the PUMA by year level. The model includes PUMA-level demographics, PUMA fixed effects, and year fixed effects. Additionally, we include demographic controls based on the cell-level averages of age, number of kids, number of kids under age 6, educational attainment, marital status, and race. We also include labor demand controls, and housing price controls at the PUMA level. The results are weighted using the number of women in each PUMA by year cell. Standard errors clustered at the PUMA level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 7: Effect of Enforcement Policies Separately on High Skill Women's Labor Supply, Women with Kids Under 6

	(1)	(2)	(3)	(4)	(5)
A: Work > 0 Hours					
Jail 287(g)	-0.901			-0.752	
	(0.614)			(0.624)	
Task 287(g)		-0.229		0.358	
		(0.890)		(0.887)	
Secure Communities			-0.918**	-0.853**	
			(0.379)	(0.389)	
Summary Index					-0.643**
					(0.263)
Mean Y	78.58	78.58	78.58	78.58	78.58
P Jail=Task				0.36	
P Jail=SC				0.90	
P SC=Task				0.22	
F Joint Sig				0.06	
N	8572	8572	8572	8572	8572
B: Usual Hours Worked					
Jail 287(g)	-0.351			-0.267	
	(0.241)			(0.247)	
Task 287(g)		0.020		0.294	
		(0.351)		(0.364)	
Secure Communities			-0.569***	-0.554***	
			(0.178)	(0.181)	
Summary Index					-0.344***
					(0.118)
Mean Y	28.47	28.47	28.47	28.47	28.47
P Jail=Task				0.27	
P Jail=SC				0.38	
P SC=Task				0.04	
F Joint Sig				0.01	
N	8572	8572	8572	8572	8572
C: Usual Hours Worked If Working					
Jail 287(g)	-0.005			0.031	
	(0.207)			(0.231)	
Task 287(g)		0.112		0.168	
		(0.283)		(0.310)	
Secure Communities			-0.261*	-0.272**	
			(0.134)	(0.137)	
Summary Index					-0.118
					(0.090)
Mean Y	36.17	36.17	36.17	36.17	36.17
P Jail=Task				0.76	
P Jail=SC				0.29	
P SC=Task				0.21	
F Joint Sig				0.25	
N	8565	8565	8565	8565	8565

Notes: Data are from the 2005-2012 American Community Survey. The sample includes all U.S.-born women with a college degree or more ages 20-64 and the data is collapsed at the PUMA by year level. The model includes PUMA-level demographics, PUMA fixed effects, and year fixed effects. Additionally, we include demographic controls based on the cell-level averages of age, number of kids, number of kids under age 6, educational attainment, marital status, and race. We also include labor demand controls, and housing price controls at the PUMA level. The results are weighted using the number of women in each PUMA by year cell. Standard errors clustered at the PUMA level. * p<0.10, ** p<0.05, *** p<0.01

Table 8: Effect of Enforcement on High Skill Women's Labor Supply
Alternative model with PUMA trends

	Work > 0 Hours	Usual Hours Worked	Usual Hours Worked If Working
A: Kids of Any Age, Baseline			
Summary Index	-0.314**	-0.180***	-0.079
	(0.134)	(0.068)	(0.051)
Mean Y	82.88	30.97	37.33
N	8576	8576	8576
B: Kids of Any Age, Pre-Treatment Trends			
Summary Index	-0.238*	-0.140**	-0.066
	(0.138)	(0.069)	(0.052)
Mean Y	82.88	30.96	37.33
N	8568	8568	8568
C: Kids any age, Detrended			
Summary Index	-0.119	-0.121	-0.104
	(0.297)	(0.142)	(0.138)
Mean Y	83.64	31.42	37.53
N	8576	8576	8576
D: Kids under 6, Baseline			
Summary Index	-0.643**	-0.344***	-0.118
	(0.263)	(0.118)	(0.090)
Mean Y	78.58	28.47	36.17
N	8572	8572	8565
E: Kids under 6, Pre-Treatment Trends			
Summary Index	-0.646**	-0.305**	-0.071
	(0.276)	(0.123)	(0.093)
Mean Y	78.57	28.46	36.17
N	8564	8564	8557
F: Kids under 6, Detrended			
Summary Index	0.064	-0.279	-0.398*
	(0.641)	(0.268)	(0.238)
Mean Y	79.41	28.88	36.31
N	8572	8572	8565

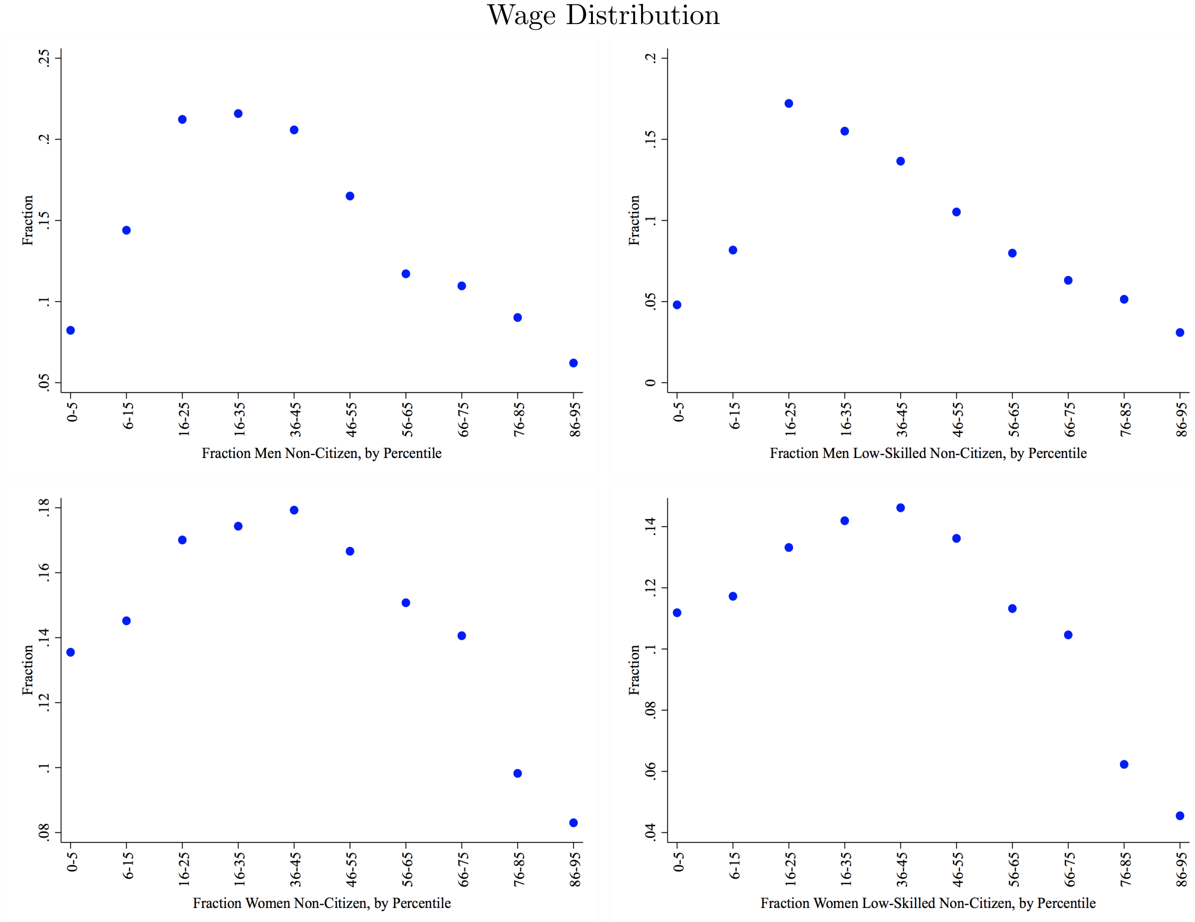
Notes: Data are from the 2005-2012 American Community Survey. The sample includes all U.S.-born women with a college degree or more ages 20-64 and the data is collapsed at the PUMA by year level. The model includes PUMA-level demographics, PUMA fixed effects, and year fixed effects. Additionally, we include demographic controls based on the cell-level averages of age, number of kids, number of kids under age 6, educational attainment, marital status, and race. We also include labor demand controls, and housing price controls at the PUMA level. The results are weighted using the number of women in each PUMA by year cell. Standard errors clustered at the PUMA level. * p<0.10, ** p<0.05, *** p<0.01

A Control Variables Description

In the baseline regressions, we include controls for labor demand as well as housing prices. We construct four Bartik-style measures of labor demand that correspond to the following four demographic groups: 1) all working-age adults, 2) foreign-born working-age adults, 3) working-age women with more than a college degree or more, and 4) working-age men with more than a college degree or more. For each group, we calculate the PUMA-level employment by industry, as a fraction of total PUMA employment in 2005. We then apply to these industry shares the changes in national employment for the full national sample of working age adults for each industry over time, to obtain a measure of predicted changes in local labor demand. The housing prices information comes from the Federal Housing Finance Agency and is available at the county by year level, which we aggregate up to the PUMA level using a similar weighting process as described in the main text for the SC and 287(g) variables.

B Additional Results

Figure 6: Fraction of Household Worker's who are Citizens or Low-Skilled Non-Citizens across the Wage Distribution



Notes: Data are from the 2005 American Community Survey. The sample includes all individuals aged 20-64 who report working in the household service industry or occupation. Fraction of workers in each wager percentile bin (0-5, 6-15, etc) that are non-citizens and low-skilled non-citizens shown. The results are weighted using the number of workers in each PUMA by year by gender cell.

Table A1: Most Serious Criminal Conviction among those Detained in 2003-2016

No Conviction	45%
Traffic	4%
Immigration	2%
DUI	6%
Marijuana (sell & possess)	2%
Other	41%

Notes: Data are from the 2003-2016 TRAC Data available here: `http://trac.syr.edu/phptools/immigration/detainhistory/`.

Table A2: Effect of Enforcement on High-Skilled Women's Fertility

	Birth Last 12 Months	Num Kids Under 5
A: Enforcement- January		
Summary Index	0.001	0.002*
	(0.001)	(0.001)
Mean Y	0.06	0.20
N	8567	8576
B: Enforcement- Fraction Current Year		
Summary Index	0.001	0.001
	(0.001)	(0.001)
Mean Y	0.06	0.20
N	8567	8576
C: Enforcement- Fraction Last Year		
Summary Index	0.000	0.002*
	(0.001)	(0.001)
Mean Y	0.06	0.20
N	8567	8576

Notes: Data are from the 2005-2012 American Community Survey. The sample includes all U.S.-born women with a college degree or more ages 20-64 and the data is collapsed at the PUMA by year level. The model includes PUMA-level demographics, PUMA fixed effects, and year fixed effects. Additionally, we include demographic controls based on the cell-level averages of age, number of kids, number of kids under age 6, educational attainment, marital status, and race. We also include labor demand controls, and housing price controls at the PUMA level. The results are weighted using the number of women in each PUMA by year cell. Standard errors clustered at the PUMA level. * p<0.10, ** p<0.05, *** p<0.01

Table A3: Effect of Enforcement on High-Skilled Women's Labor Supply, Additional Outcomes

	Work > 50 Hours	Work > 60 Hours	Work > 50 Hours if Working	Work > 60 Hours if Working
A: Full Sample				
Summary Index	-0.099	-0.094*	-0.064	-0.097
	(0.090)	(0.052)	(0.105)	(0.061)
Mean Y	14.59	4.50	17.05	5.26
N	8576	8576	8576	8576
B: Kids of Any Age				
Summary Index	-0.147	-0.074	-0.127	-0.086
	(0.115)	(0.071)	(0.139)	(0.088)
Mean Y	12.19	3.51	14.75	4.25
N	8576	8576	8576	8576
C: Kids Under 6				
Summary Index	-0.205	-0.029	-0.129	-0.015
	(0.179)	(0.107)	(0.227)	(0.138)
Mean Y	9.69	2.46	12.41	3.16
N	8572	8572	8565	8565

Notes: Data are from the 2005-2012 American Community Survey. The sample includes all U.S.-born women with a college degree or more ages 20-64 and the data is collapsed at the PUMA by year level. The model includes PUMA-level demographics, PUMA fixed effects, and year fixed effects. Additionally, we include demographic controls based on the cell-level averages of age, number of kids, number of kids under age 6, educational attainment, marital status, and race. We also include labor demand controls, and housing price controls at the PUMA level. The results are weighted using the number of women in each PUMA by year cell. Standard errors clustered at the PUMA level. * p<0.10, ** p<0.05, *** p<0.01

Table A4: Effect of Enforcement on High Skill Women's Labor Supply, Alternative Level of Geography

	Labor Force Participation	Usual Hours Worked	Usual Hours Worked If Working
A: Kids of Any Age, PUMA			
Summary Index	-0.314**	-0.180***	-0.079
	(0.134)	(0.068)	(0.051)
Mean Y	82.88	30.97	37.33
N	8576	8576	8576
B: Kids of Any Age, PUMA for County Obs Only			
Summary Index	-0.121	-0.138	-0.117
	(0.217)	(0.105)	(0.076)
Mean Y	81.95	30.62	37.32
N	3839	3839	3839
C: Kids of Any Age, County			
Summary Index	-0.050	-0.118	-0.122*
	(0.231)	(0.110)	(0.067)
Mean Y	81.95	30.62	37.33
N	1748	1748	1748
D: Kids Under 6, PUMA			
Summary Index	-0.643**	-0.344***	-0.118
	(0.263)	(0.118)	(0.090)
Mean Y	78.58	28.47	36.17
N	8572	8572	8565
E: Kids Under 6, PUMA for County Obs Only			
Summary Index	0.171	-0.102	-0.187
	(0.377)	(0.177)	(0.145)
Mean Y	77.63	28.22	36.29
N	3836	3836	3830
F: Kids Under 6, County			
Summary Index	0.317	-0.055	-0.193
	(0.372)	(0.217)	(0.177)
Mean Y	77.63	28.22	36.30
N	1748	1748	1748

Notes: Data are from the 2005-2012 American Community Survey. The sample includes all U.S.-born women with a college degree or more ages 20-64 and the data is collapsed at the geographic area (PUMA or county) by year level. The model include geographic area level demographics, geographic fixed effects, and year fixed effects. Additionally, we include demographic controls based on the cell-level averages of age, number of kids, number of kids under age 6, educational attainment, marital status, and race. We also include labor demand controls, and housing price controls at the geographic area level. The results are weighted using the number of women in each geographic area by year cell. Standard errors clustered at the geographic area level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table A5: Effect of Enforcement on High-Skilled Women's Labor Supply, Robustness to Timing

	Work > 0 Hours	Usual Hours Worked	Usual Hours If Working
A: Any Kids, January			
Summary Index	-0.314**	-0.180***	-0.079
	(0.134)	(0.068)	(0.051)
Mean Y	82.88	30.97	37.33
N	8576	8576	8576
B: Any Kids, Fraction Current Year			
Summary Index	-0.282*	-0.132*	-0.042
	(0.144)	(0.073)	(0.062)
Mean Y	82.88	30.97	37.33
N	8576	8576	8576
C: Any Kids, Fraction Last Year			
Summary Index	-0.237*	-0.170**	-0.096
	(0.142)	(0.074)	(0.058)
Mean Y	82.88	30.97	37.33
N	8576	8576	8576
D: Kids Under 6, January			
Summary Index	-0.643**	-0.344***	-0.118
	(0.263)	(0.118)	(0.090)
Mean Y	78.58	28.47	36.17
N	8572	8572	8565
E: Kids Under 6, Fraction Current Year			
Summary Index	-0.308	-0.192	-0.091
	(0.307)	(0.128)	(0.106)
Mean Y	78.58	28.47	36.17
N	8572	8572	8565
F: Kids Under 6, Fraction Last Year			
Summary Index	-0.709***	-0.316**	-0.030
	(0.271)	(0.123)	(0.097)
Mean Y	78.58	28.47	36.17
N	8572	8572	8565

Notes: Data are from the 2005-2012 American Community Survey. The sample includes all U.S. citizen women with a college degree or more ages 20-64 and the data is collapsed at the PUMA by year level. The model includes PUMA-level demographics, PUMA fixed effects, and year fixed effects. Additionally, we include demographic controls based on the cell-level averages of age, number of kids, number of kids under age 6, educational attainment, marital status, and race. We also include labor demand controls, and housing price controls at the PUMA level. The results are weighted using the number of women in each PUMA by year cell. Standard errors clustered at the PUMA level. * p<0.10, ** p<0.05, *** p<0.01

Table A6: Effect of Enforcement on High Skill Women's Labor Supply, Robustness to Dropping Early Adopter SC

	Work > 0 Hours	Usual Hours Worked	Usual Hours If Working
A: Kids of Any Age, Full Sample			
Summary Index	-0.314**	-0.180***	-0.079
	(0.134)	(0.068)	(0.051)
Mean Y	82.88	30.97	37.33
P Jail=Task	8576	8576	8576
B: Kids of Any Age, Drop Early Adopter SC			
Summary Index	-0.388*	-0.283**	-0.178**
	(0.222)	(0.111)	(0.081)
Mean Y	83.28	30.93	37.10
N	7336	7336	7336
C: Kids Under 6, Full Sample			
Summary Index	-0.643**	-0.344***	-0.118
	(0.263)	(0.118)	(0.090)
Mean Y	78.58	28.47	36.17
N	8572	8572	8565
D: Kids Under 6, Drop Early Adopter SC			
Summary Index	-0.795	-0.511**	-0.271*
	(0.487)	(0.220)	(0.148)
Mean Y	79.00	28.43	35.92
N	7333	7333	7329

Notes: Data are from the 2005-2012 American Community Survey. The sample includes all U.S.-born women with a college degree or more ages 20-64 and the data is collapsed at the PUMA by year level. The model includes PUMA-level demographics, PUMA fixed effects, and year fixed effects. Additionally, we include demographic controls based on the cell-level averages of age, number of kids, number of kids under age 6, educational attainment, marital status, and race. We also include labor demand controls, and housing price controls at the PUMA level. The results are weighted using the number of women in each PUMA by year cell. Standard errors clustered at the PUMA level. * p<0.10, ** p<0.05, *** p<0.01

Table A7: Effect of Enforcement on High Skill Women's Labor Supply, Robustness to Alternative Housing Price Controls

	Work > 0 Hours	Usual Hours Worked	Usual Hours Worked If Working
A: Kids of Any Age, Baseline			
Summary Index	-0.314**	-0.180***	-0.079
	(0.134)	(0.068)	(0.051)
Mean Y	82.88	30.97	37.33
N	8576	8576	8576
B: Kids of Any Age, State Housing Prices			
Summary Index	-0.308**	-0.178***	-0.080
	(0.136)	(0.068)	(0.052)
Mean Y	82.88	30.97	37.33
N	8576	8576	8576
C: Kids of Any Age, State Leave Out PUMA Housing Prices			
Summary Index	-0.293**	-0.174***	-0.082
	(0.136)	(0.067)	(0.051)
Mean Y	82.86	30.97	37.34
N	8552	8552	8552
D: Kids Under 6, Baseline			
Summary Index	-0.643**	-0.344***	-0.118
	(0.263)	(0.118)	(0.090)
Mean Y	78.58	28.47	36.17
N	8572	8572	8565
E: Kids Under 6, State Housing Prices			
Summary Index	-0.608**	-0.332***	-0.121
	(0.267)	(0.119)	(0.091)
Mean Y	78.58	28.47	36.17
N	8572	8572	8565
F: Kids Under 6, State Leave Out PUMA Housing Prices			
Summary Index	-0.572**	-0.322***	-0.125
	(0.270)	(0.120)	(0.091)
Mean Y	78.57	28.48	36.20
N	8548	8548	8541

Notes: Data are from the 2005-2012 American Community Survey. The sample includes all U.S.-born women with a college degree or more ages 20-64 and the data is collapsed at the PUMA by year level. The model includes PUMA-level demographics, PUMA fixed effects, and year fixed effects. Additionally, we include demographic controls based on the cell-level averages of age, number of kids, number of kids under age 6, educational attainment, marital status, and race. We also include labor demand controls, and housing price controls at the PUMA level. The results are weighted using the number of women in each PUMA by year cell. Standard errors clustered at the PUMA level. * p<0.10, ** p<0.05, *** p<0.01

Table A8: Effect of Enforcement on Migration Rates

	High-Skilled Citizen Women Kids of Any Age	High-Skilled Citizen Women Kids <6	Low-skilled Non-citizen Women	Low-skilled Non-citizen Men	Household Workers Non-citizen Women	Household Workers Non-citizen Men
Summary Index	5.788	0.970	-1.674	-4.035	0.360	0.329
	(6.638)	(4.026)	(1.910)	(3.282)	(0.821)	(0.529)
Y mean	265.45	132.76	34.60	47.53	7.24	2.29
Observations	8576	8576	8576	8576	8576	8576

Notes: Data are from the 2005-2012 American Community Survey. The sample is based on all working-age (20-64) individuals. The model includes PUMA-level demographics, PUMA fixed effects, and year fixed effects. Additionally, we include demographic controls based on the cell-level averages of age, number of kids, number of kids under age 6, educational attainment, marital status, and race. We also include labor demand controls, and housing price controls at the PUMA level. The results are weighted using the number of women in each PUMA by year cell. Standard errors clustered at the PUMA level. * p<0.10, ** p<0.05, *** p<0.0