Changes in Local Labor Markets and Inventor Productivity: Evidence from a major policy from 2008 to 2013

Fangfang Du, Yinghua Li, and Jessie Jiaxu Wang*

Abstract

This paper examines how changes in local labor markets influence inventor productivity, leveraging the staggered rollout of a major policy that affected labor supply in household services. We hypothesize that by altering the availability of household services labor, the policy indirectly impacted time allocation among inventors. Our analysis reveals that after the policy rollout, productivity declines were more pronounced among a specific group of inventors. These effects were particularly evident for inventors balancing professional and household responsibilities, while those with stronger professional networks or access to workplace accommodations were less affected. Our findings contribute to the broader understanding of how labor market shifts shape high-skill innovation outcomes.

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* Du, fangfangdu@fullerton.edu, College of Business and Economics, California State University Fullerton; Li, yinghua.li@asu.edu, W.P. Carey School of Business, Arizona State University; and Wang, jessiejiaxuw@gmail.com.
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1. Introduction

The gender gap in the labor market remains a persistent issue, with women often facing underrepresentation, lower earnings, and barriers to career advancement (Goldin 1990, 2006, 2014). Even wider than the broad labor market disparity is the gender gap in inventions. Despite increasing female participation in innovation, patenting remains male-dominated. Analysis of USPTO data from 1975 to 2021 reveals that only 13% of all inventors are female, over 82% of patent applications originate from all-male inventor teams, and a staggering 97% involve at least one male inventor. Given the far-reaching implications of the persistent gender gap in inventive activities and the alarming claim that the world is designed primarily for men (Criado Perez, 2019), it is crucial to understand the root causes to enhance inclusivity in patenting and inform effective policy design.[1]

This paper examines a previously unexplored driver of the inventor gender gap—immigration enforcement policies and the resulting shifts in the supply of undocumented immigrants in household services. Our approach is novel in two key aspects. First, we leverage an immigration enforcement change, the staggered rollout of the Secure Communities (SC) program from 2008 to 2013, which imparted a negative shock to the supply of undocumented immigrant labor in household services. Second, the granular inventor-level data enable us to directly measure each inventor's productivity, linking it to factors including personal traits (e.g., age, track record, collaborative relationship), employer characteristics, and local labor market conditions.

Prior research indicates that women typically allocate more time to household chores and childcare than men (Cortés and Tessada, 2011; Cortés and Pan, 2013; 2019). Consequently, women are more susceptible to shifts in the availability and cost of household services. If stricter immigration enforcement policies reduce the labor supply of household services, these measures could potentially exacerbate the productivity gap between male and female inventors.

To study the effect of stricter immigration enforcement policies on the inventor gender gap, we exploit the staggered rollout of the SC program from 2008 to 2013. The SC program was a

[1] The low participation of women in innovation can discourage young women from becoming inventors due to a lack of mentors and role models (Bell et al. 2019). This underrepresentation may also lead to the underproduction of certain types of inventions, such as those that focus on female welfare and health outcomes (Koning, Samila, and Ferguson, 2020; Criado Pérez, 2020).

large-scale, mandatory federal immigration enforcement initiative that increased the threat of deportation for undocumented immigrants without a direct intention to impact innovation outcomes. Prior literature generally concludes that the timing of SC's staggered rollout across counties is plausibly exogenous (Cox and Miles, 2013; East, Hines, Luck, Mansour, and Velásquez, 2023). Over 454,000 individuals were removed under SC during 2008–2014, and many more withdrew from the labor market due to the program's "chilling effects."

Since undocumented immigrants labor contributes to a significant portion of household services, SC presumably had a negative impact on the availability of these services. This setting allows us to identify the causal effect of immigration enforcement policies on the gender gap in invention through changes in the availability of household services. If the reduced availability of household services disproportionately affects the labor supply and time allocation of female inventors, we expect to observe a widening gender gap in inventor productivity after the SC implementation.

Our analysis employs a granular inventor-by-year panel dataset in conjunction with the rollout dates of the SC program. This method connects inventors' patenting outcomes to their geographical locations, where local labor market conditions for household services were differentially affected by the phased implementation of SC. Specifically, using the variation in the timing of SC's rollout across counties and over time, we estimate a staggered difference-in-differences model to identify the effect of immigration enforcement on the gender gap in patenting outcomes.

Our baseline Poisson regressions reveal that while patenting productivity decreased among both male and female inventors, the decline in productivity was notably greater for female inventors than for their male counterparts. Specifically, compared with male inventors, female inventors experienced a 24% greater decline in the number of patent filings, a 30% greater decline in patent citations, a 25% greater decline in the likelihood of filing high-impact patents, and a 21% greater decline in the market value of patents. These results suggest that the gender gap in innovation widened following SC's rollout.

Our proposed economic interpretation is that tougher immigration enforcement reduced the supply of undocumented immigrants in household services, thereby increasing the costs for female inventors to outsource household production. This, in turn, diverted their time and effort away from inventive activities. To provide evidence on this mechanism, we first validate the effect of SC on the availability of household services, we document a significant decline in the labor supply of household workers likely to be undocumented immigrants in counties that adopted SC, while the labor supply of lawful household workers remained largely unchanged.

To confirm that the decreased supply of undocumented labor in household services is indeed a channel through which SC widened the gender gap in innovation, we examine how patenting productivity for male and female inventors responded differently to changes in the availability of undocumented labor in household services. Specifically, we compute the county-level decline in undocumented labor in household services due to the SC rollout and then examine whether this is associated with the gender gap in inventors' productivity. Our estimates show that SC led to an 8.9% reduction in the employment of likely undocumented immigrants in household services, relative to the sample mean; this change in turn translates to a 44.1% decline in the number of patents among female inventors, compared with a 34.4% decline among male inventors. In comparison, a falsification test using undocumented immigrant employment in agriculture and construction, rather than household services, reveals no significant impact on the gender gap in innovation. Collectively, these results highlight the labor supply of undocumented immigrants in household services as an important channel through which stricter immigration enforcement policies widen the inventor gender gap.

We conduct a series of cross-sectional analyses to corroborate the notion that SC influenced the gender gap in innovation through its impact on the availability of household services. Specifically, we find that the differential effect of SC on the productivity of female versus male inventors was more pronounced for female inventors (i) in their childbearing and rearing years, when family responsibilities disproportionately fall on women; (ii) with a weak track record, who may lack the adaptability and resources needed to cushion against career disruptions; (iii) without strong collaborative relationships, which would otherwise allow them to rely on collaborators during disruptions and constrained times; (iv) working at firms with workplace policies rated as not female-friendly.

We perform a battery of robustness tests to validate our findings. First, our results remain robust when applying a stacked difference-in-differences model which accounts for treatment effect heterogeneity. Second, to address concerns about pre-trends, we analyze the dynamics of the gender gap in patenting in relation to SC's adoption and find that the divergent declines in patenting between genders did not manifest before the activation of SC and persisted in the years following SC's activation. Third, our results hold well across various fixed-effects specifications, inventor-level regressions, and alternative measures of patenting productivity. For instance, we find that SC's passage is significantly associated with a higher likelihood of inventor attrition, with a notably stronger effect among female inventors. Finally, we confirm that our findings are not driven by other local immigration enforcement policies, early SC-adopting counties, counties bordering Mexico, or direct effects on Hispanic inventors.

Overall, our study reveals an unintended consequence of immigration enforcement policies: By shifting the availability of household services provided by low-skilled undocumented immigrants, these policies disproportionally influenced the time allocation and productivity of high-skilled female inventors. Our findings thus offer insights for policymakers aiming to narrow the gender gap in inventive activities.

A key contribution of this paper is providing the first causal evidence on the role of immigration enforcement policy in the gender gap in innovation. Existing literature has documented a large and persistent gender gap in innovation, underscoring the need to narrow this disparity. Some note the role of gender differences in education and research focus (Moser and Lubczyk, 2024); others highlight the influence of role models, suggesting that an increase in women inventors encourages more women to pursue STEM and engage in innovation (Kahn and Ginther, 2017; Bell et al., 2019).[2] Our study adds to this literature by identifying immigration enforcement as a novel factor influencing the gender gap in innovation.

More broadly, this paper adds to the literature on gender gaps in labor market outcomes. Goldin's seminal contributions (1990, 2006, 2014) examined various aspects of gender disparities in the labor market, spanning participation rates, earnings, and career progression. Her framework emphasizes that the constraints women face in balancing work and family are crucial to their labor

[2] Our paper also contributes more broadly to the literature identifying factors that influence the inventive productivity in general. Some studies argue for the importance of characteristics at birth, such as race, gender, and parents' socioeconomic class and income (Bell et al., 2019), while others emphasize early exposure and role models, social and family interactions (Aghion et al., 2018), educational experiences, especially those in STEM related fields (e.g., Toivanen and Väänänen, 2016; Kahn and Ginther, 2017; Wood, 2020).

market outcomes. Building on this foundation, Cortés and Tessada (2011) and Cortés and Pan (2013, 2019) further show that services provided by low-skilled immigrants serve as substitutes for household production, allowing high-skilled women to adjust their time-use decisions. Our results align with these findings, affirming that high-skilled women continue to face significant challenges in reconciling family obligations with professional pursuits. We extend these earlier studies by zooming in on female inventors and assessing how a major immigration enforcement policy affected the gender gap in invention by altering the supply of low-skilled immigrant labor.

Our paper also relates to recent studies on the gender gap in productivity amid the COVID-19 pandemic among high-skilled labor. Using a survey, Barber, Jiang, Morse, Puri, Tookes, and Werner (2021) find that research productivity in finance falls more for women and faculty with young children. Cui, Ding, and Zhu (2022) report that female academics' productivity dropped by more than that of male academics 10 weeks amid the lockdown in the U.S. Further, Li and Wang (2021) and Du (2023) find that the pandemic disproportionately affects female equity analysts in the quality of their forecasts, especially those likely in parenthood. Unlike the pandemic, which introduced many dimensions of shocks and had various economic channels at play, our setting of SC allows us to focus on a specific channel: the supply of undocumented labor in household services in the context of the SC program.

Finally, our paper contributes to the policy discussions on immigration enforcement. While a small set of earlier studies have examined the effects of the SC program on Hispanic citizens' participation in safety net programs (Alsan and Yang, 2022), immigrants' health outcomes (Wang and Kaushal, 2019), marriage patterns (Bansak and Pearlman, 2021), and local crime rates (Miles and Cox, 2014; Hines and Peri, 2019), our findings reveal an unintended consequence of this immigration enforcement policy: its negative impact on the productivity gender gap of inventors. This adverse effect, resulting from the concentration of undocumented immigrants in household services, highlights a nuanced dimension of immigration enforcement. Relatedly, East and Velásquez (2022) find that the SC program reduced the hours worked of college-educated, U.S.-born mothers with young children. Like their analysis, we attribute the differential impact on male and female workers to an increase in the cost of outsourcing household production. However, our paper focuses on inventors and directly identifies the effects of the SC program on the gender gap in productivity by examining quantity, quality, and patent market value. In this way, our study complements East and Velásquez (2022) by providing distinct evidence on the unintended impacts of the SC program on skilled women.

The remainder of the paper is structured as follows. Section 2 discusses the institutional background of the Secure Communities program and presents our conceptual framework. Section 3 outlines the data and presents summary statistics. Section 4 estimates the differential effects of the SC on the patenting outcomes of male and female inventors. Section 5 provides evidence on the economic mechanism through the supply of undocumented immigrant labor in household services. Section 6 concludes.

2. Institutional Background and Conceptual Framework

To examine the impact of stricter immigration enforcement policies on the gender gap in invention, we exploit a large federal policy change—the Secure Communities (SC) program, which was implemented across counties between 2008 and 2013 and led to an increased risk of deportation for undocumented immigrants.

2.1 The Secure Communities (SC) program

The SC program was one of the largest mandatory federal immigration enforcement actions administered by Immigration and Customs Enforcement (ICE).[3] Prior to the SC program's introduction in late 2008, immigration enforcement was a labor-intensive process primarily managed by federal ICE agents. Although there were two earlier federal-local partnerships, they accounted for only a small fraction of all police jurisdictions.[4] The SC program aimed to enhance information sharing between local law enforcement agencies and the federal government, streamlining the detection and removal process for undocumented immigrants.

Under the SC program, the process of screening arrestees for their immigration status became significantly less labor-intensive. Fingerprints collected during booking at jails, previously sent only to the Federal Bureau of Investigations (FBI) for criminal background checks, were now

[3] For reviews of the SC program, see Cox and Miles (2013), Miles and Cox (2014), and Alsan and Yang (2022).
[4] Under section 287(g) agreements with the Department of Homeland Security (DHS), state and local officers with ICE training checked for documentation status upon booking arrestees into jail as part of routine policing operations, such as traffic stops. Under the Criminal Alien Program, federal ICE officers stationed in federal, state, and local jails and prisons would screen inmates for documentation status. In the absence of either program, local officers could still request ICE assistance if they suspected an arrestee might be deportable (Capps et al., 2011; Cox and Miles, 2013).

also forwarded to the Department of Homeland Security (DHS). DHS cross-checked these fingerprints with its Automated Biometric Identification System database, which includes the fingerprints of all noncitizens previously recorded by DHS. If a match was found, ICE would determine whether the arrestee was in violation of immigration law and decide whether to place a detainer to initiate deportation proceedings. Importantly, the SC program required no additional action from local agencies. As a result, undocumented immigrants arrested under the SC program faced a substantially higher likelihood of being apprehended and deported by ICE.

Due to resource and technical constraints, the SC program could not be implemented across the entire U.S. all at once. Instead, it was rolled out on a county-by-county basis between October 27, 2008, and January 22, 2013, with most of the rollout concentrated between 2010 and 2012. By 2013, all counties had adopted the program. It is important to note that the federal government determined the timing of each county's SC activation, and no county could opt in, opt out, or forego immigration screening. The order of the rollout was thus entirely at the discretion of the federal government (Cox and Miles, 2013; Miles and Cox, 2014). Once activated, the SC program remained in place in a county until it was discontinued nationwide in November 2014.[5]

Figure 1 illustrates the county-by-county rollout of the SC program. Existing literature generally agrees that the timing of this staggered rollout across counties appears largely random and unrelated to a county's economic development or political characteristics. East et al. (2023) find no evidence that the timing of SC's activation in a local area can be predicted by pre-SC changes in demographic and economic characteristics. Their distributed lag analyses reveal no significant trends in labor market outcomes before SC implementation, leading them to conclude that the timing of SC implementation is plausibly exogenous. Similarly, Cox and Miles (2013) show that, with the exception of a few *initial* SC activations, later activations became more

[5] The broad reach of SC and the disruption it caused to immigrant communities led several local jurisdictions, known as sanctuary cities, to refuse to cooperate with ICE detainer requests, arguing that these requests were unconstitutional under the Fourth Amendment (Alsan and Yang, 2022). At the end of 2014, the SC program was replaced by the Priority Enforcement Program (PEP). Although PEP continued the same screening process as SC, it shifted focus to individuals convicted of serious crimes or those deemed a threat to public safety. The SC program was reactivated in 2017 but suspended again in 2021.

"random" as it became common for multiple inactive counties within the same state to be activated simultaneously on the same date.[6]

2.2 Effect on undocumented immigrant labor

Prior literature on the SC program consistently confirms that it increased the probability of deportation for undocumented immigrants (Miles and Cox, 2014; Alsan and Yang, 2022; East and Velásquez, 2022; East et al., 2023). We argue that stringent immigration enforcement, such as SC, engenders a climate of fear among undocumented immigrant workers, leading to their reduced labor force participation and employment, particularly in sectors heavily reliant on undocumented labor.

Between 2008 and 2014, over 454,000 individuals were deported under SC, with 21% having no criminal convictions and 61% having non-violent crimes as their most serious offense. This highlights how SC heightened the risk of deportation for non-violent and otherwise law-abiding undocumented immigrants. Beyond deportations, SC also generated "chilling effects" among immigrant workers who remained in the U.S., as fear of interacting with law enforcement or needing to present identification likely increased the costs of job search and working outside the home. Valdivia (2019) shows that this fear discourages undocumented immigrants from going to work, while Amuedo-Dorantes and Antman (2022) find that stringent enforcement reduced labor force participation and employment among likely undocumented immigrants, particularly women. East et al. (2023) further document declines in employment rates and wages for these likely undocumented workers.[7] Additionally, SC may have contributed to voluntary out-migration or reduced in-migration of undocumented immigrants.

As discussed earlier, we are particularly interested in exploiting SC's effect on undocumented immigrant workers in household service occupations. We conjecture that SC's rollout created a negative shock to the labor supply in this sector, where undocumented immigrants

[6] While the few early adoptions were associated with factors such as the proportion of the county's Hispanic population, proximity to the U.S.-Mexico border, and the presence of local 287(g) agreements, they were not selected based on economic performance, crime rates, or political support for SC.
[7] As an illustration of the fear induced by the SC program, Alsan and Yang (2022) observe reductions in food stamp and SSI take-up even among U.S. citizen Hispanic Americans driven by deportation fears.

constitute a significant portion of the workforce.[8] By 2008, before SC's implementation, an estimated 8 million undocumented immigrants were working in the U.S., making up 5.4% of the entire labor force (Passel and Cohn, 2016). Undocumented workers are particularly concentrated in household services—according to the 2005 American Community Survey, 19% of workers in private households were undocumented, surpassing sectors like agriculture (17%), construction (11%), and manufacturing (7%). Within private households, most undocumented immigrants work in household service occupations, with 77% working as maids and housekeeping cleaners, and an additional 12% in childcare roles.[9] These figures suggest that household services are especially vulnerable to disruptions in the availability of undocumented immigrant labor following stringent immigrant policies. In Section 5.1, we empirically validate that the rollout of SC is indeed associated with a significant decline in the supply of undocumented labor in household services.

2.3 Effect on the gender gap in innovation

In this section, we lay out our arguments for why and how SC might affect the gender gap in inventive activities. We argue that because women typically allocate more time to household chores and childcare than men, they are more susceptible to shifts in the availability and cost of household services. Therefore, tougher immigrant enforcement policies could further widen the productivity gap between male and female inventors by reducing the labor supply of household services.

Our conceptual framework is rooted in Claudia Goldin's seminal research, particularly her work on factors influencing women's labor market decisions and outcomes. Goldin's framework (1990, 2006, 2014), which interweaves education, parenthood, and productivity, highlights the more binding constraints women face in making labor supply decisions compared with men. One key constraint is women's greater need to balance work and family responsibilities, which plays a crucial role in creating gender gaps in labor market outcomes. Goldin's research also underscores

[8] Household services include various work that help people maintain the household. For instance, a household needs someone to cook and clean, mow the lawn, and babysit the kids. Ability to outsource these tasks can significantly relax the time constraint of household members, especially females.

[9] There are many reasons why private households may have an incentive to hire undocumented immigrants. Undocumented immigrants are often perceived to have lower reservation wages (Bailey, 1985; Rivera-Batiz, 1999; Kossoudji and Cobb-Clark, 2002; Pan, 2012; Albert, 2021; East et al., 2023). Additionally, by hiring undocumented immigrants for domestic work, private households could avoid paying Social Security and Medicare taxes on wages for their employees.

the observed significant gender gap in labor market outcomes among those who are married. Within a household, domestic responsibilities often fall disproportionately on women and require them to navigate the dual demands of their careers and family duties, thereby constraining their choices in labor market participation and time allocation.[10]

In this context, the labor supply of low-skill immigrants in household services serves as a substitute for high-skilled women's domestic work, while complementing their professional endeavors. Consequently, if the SC program reduces the labor supply in household services and makes domestic help less accessible and affordable, it could have a disproportionately adverse impact on the labor supply and time allocation of female inventors, thereby exacerbating the gender gap in inventor productivity.

3. Sample Construction and Summary Statistics

The analysis combines inventor-level patent data with the rollout dates of the SC program. To construct inventor-level patenting outcomes, we use data from PatentsView's disambiguated inventor database, which compiles information from the USPTO.[11] This database assigns each inventor a unique, time-invariant ID, allowing us to track individual inventor's patent output and geographical location. The dataset includes comprehensive information on every USPTO patent from 1976 to 2018, such as application and grant years, patent technology class, and extensive citation data. Importantly, PatentsView also provides detailed inventor information, including the inventor's name, gender (predicted by algorithm), assignee name, and residential address.[12]

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[10] According to a time-use survey sponsored by the Bureau of Labor Statistics (BLS), in U.S. households consisting of married or cohabiting parents and one or more children under the age of 18, 80% of mothers say they are the household member who usually prepares the meals – the same as the share who say they are the primary grocery shopper, according to a Pew Research Center analysis. Some 71% of mothers say they primarily handle both chores. This compares with about 20% fathers in this type of household who say they are the person who usually prepares the meals (19%) or grocery shops (20%). About one-in-ten (11%) say they are the one who usually does both tasks. In households consisting of two married or cohabiting adults and no children, men and women fill less of their time with these chores – but women still report spending more time in the kitchen. Overall, women spend 52 minutes a day on meal prep, vs. 22 minutes for men.

[11] This database can be accessed at https://patentsview.org/download/data-download-tables.

[12] The algorithm to predict inventor gender employs the gender-it package developed by the World Intellectual Property Organization, which draws on data from their Worldwide Gender-Name Dictionary 2.0. This method relies on country-specific lists that assign approximate probabilities to each gender based on names within that country. For example, a person in the U.S. named "Charlie" has a 90% probability of being male and a 10% chance of being female.

Following prior literature, we define an inventor's employer as the firm listed as the assignee on the patent. Thus, an inventor who files a patent with Firm A in 2006 and another with Firm B in 2007 is considered an employee of Firm A in 2006 and of Firm B in 2007. If more than a year elapses between patent filings by the same inventor, we follow the convention in the literature and assume the inventor changes employers at the midpoint between the two patent application years (e.g., Song, Almeida and Wu, 2003). We use the residential address listed in an inventor's patent filings to impute their residential address for each year, applying the same method. Additionally, we obtain inventor age information from Kaltenberg, Jaffe, and Lachman (2021), who scraped the data from publicly available online directories. This approach enables the construction of an inventor-year panel, providing observations on an inventor's innovative output, gender, age, employer, and residential address, thereby linking patenting outcomes to inventors' geographical location and local labor market conditions for household services.

We construct several variables to capture each inventor's characteristics. These include a dummy variable, *Female*, indicating whether the inventor is female; a dummy variable, *Parenthood*, indicating whether the inventor is at childbearing and rearing age (between 31 and 45);[13] a variable *Track record*, to represent the past productivity of the inventor (the number of patents filed by and granted to the inventor in the past three years); a dummy variable, *Collaboration*, indicating whether the inventor has filed more collaborative patents in the past three years than the sample median; and a dummy variable, *Female-friendly firm*, indicating whether the inventor works for a firm whose InHerSight rating is in the top quartile for workplace hour flexibility (used as a proxy for whether the firm is perceived as female-friendly based on its ability to provide flexible work hours).

We utilize various patent-based measures to evaluate innovation productivity at the individual inventor level. The first measure focuses on patent quantity, using *Total patents*, calculated as the number of patents filed by (and subsequently granted to) an inventor in a given year. We use patent filing dates as there is typically a time gap between the application and grant years. If a patent is filed by a team of inventors, we assign that patent to each inventor. The second set of measures assesses the quality or impact of an inventor's patents based on future citations

[13] Our results are robust to various alternative definitions of this age bracket, such as between 25 and 45, and between 28 and 48.

that the patents receive. Specifically, *Citations* equals the number of citations received by all patents filed by (and granted to) an inventor in a given year; *Scaled citations* equals *Citations* scaled by the average number of citations received by patents filed in the same year and CPC technology sub-class. We scale the raw citations to account for potential variation in citation rates over time and across technologies (Bernstein, 2015) and to address truncation bias, which occurs when patents granted towards the end of the sample have less time to accumulate citations (Hall, Jaffe, and Trajtenberg, 2005). To assess the quality of an average patent, we divide the above citation measures by *Total patents* to obtain *Citations per patent* and *Scaled citations per patent*.

We also consider the position of each patent within the patent citation distribution. Given that high-risk, high-reward exploratory innovations are more likely to be situated at the tail of the patent citation distribution (Balsmeier et al., 2017), we define "high-impact innovations" as those patents that receive citations within the highest decile of patents in the same application year and CPC technology sub-class (*Top 10% cited patent*). In addition to citation-based measures of patent quality, we evaluate patent quality using the Kogan, Papanikolaou, Seru, and Stoffman (2017) measure of patent *Market value*, which is based on the stock price reaction to the announcement of a new patent grant. This measure is available only for a subset of the patents, specifically those with a publicly listed assignee.

To provide evidence on the mechanism and to validate the effect of the SC program on the availability of household services, we gather the rollout dates of SC across counties from ICE and compile data on the employment of likely undocumented immigrants in household service occupations (Occupations: 399021-Personal Care Aides; 372012-Maids and Housekeeping Cleaners; 399011-Childcare Workers) for each county-year. Consistent with previous research (e.g., East et al., 2023, Bansak and Pearlman, 2022, Jung and Mockus, 2023), we identify likely undocumented immigrants as foreign-born individuals with less than a high school degree based on the American Community Survey (ACS).[14] This sample of "low-educated foreign-born" individuals is expected to effectively capture a significant portion of the undocumented immigrant

[14] Because documentation status is not directly asked by any large-scale surveys or public dataset, different papers use slightly different definitions to identify immigrants who are likely undocumented. East and Velásquez (2022) and Amuedo-Dorantes, Churchill, and Song (2022) identify likely undocumented immigrants as Hispanics born in Mexico or Central America with less than a high school degree, while East et al. (2023) identify them as foreign-born individuals with a high school degree or less. Our results remain robust across these alternative definitions.

labor force directly affected by SC. To construct the variable *Employment of likely undocumented immigrants in household service occupations* for each county-year, we use the annual hours worked in private households by likely undocumented immigrants, scaled by the county's population in 2005—one year before our sample period begins and three years before the first county activation of the SC program.[15] Both variables are collected from the ACS database.

To identify the impact of the SC program on the productivity of inventors, we merge the PatentView database with the staggered county-level rollout dates of SC. This generates an annual inventor-level panel that combines inventor characteristics, patenting activity, the rollout status of SC in the county where the inventor resides, and the local labor supply of undocumented labor in household services around SC rollout.

Our final sample covers the period from 2006, two years before the initial SC rollout, to 2015, two years after its nationwide implementation and just after its discontinuation nationwide. We end the sample in 2015 to avoid confounding effects from the 2017 re-activation of the SC program (later suspended again in 2021). To ensure that inventors in our sample are "active," we require that each inventor has filed at least one patent within three years before SC's implementation.[16] To mitigate the influence of outliers, we winsorize all continuous variables at the 1st and 99th percentiles each year. Our main sample is a balanced panel with 3,192,690 inventor-year observations, 319,269 unique inventors, and 972,249 unique patents.

Table 1 presents summary statistics for the key variables. On average, an inventor files (and is subsequently granted) 0.61 patents annually, indicating a pattern of sparse distribution. These patents, on average, receive 4.49 citations from other patents. When scaled by the average number of citations received by patents filed in the same year and technology sub-class, this figure stands at 0.73. For patents matched to a publicly listed assignee with available patent market value, the average value in real dollars of patents filed by (and eventually granted to) an inventor each year is $4.13 million. Approximately 12.1% of inventor-years are associated with female

[15] Using the 2005 population as the denominator ensures that changes in the labor supply measure reflect actual changes in hours worked by undocumented immigrants, rather than shifts in population size. Prior literature has also used the population in a pre-SC year as the denominator to avoid potential biases from endogenous population changes (Hines and Peri, 2019; Jung and Mockus, 2023; East et al., 2023).
[16] Our sample thus does not include new inventors who entered the patent database after SC's activation.

inventors, and around 54.7% of inventor-years have a residential address in a county that adopted the SC program. Detailed definitions for all variables are available in Appendix A.

[Table 1 about here]

4. The Secure Communities program and Inventor Gender Gap

4.1 Identification strategy

Our empirical strategy exploits the variation in the timing of SC implementation and estimates a difference-in-differences model to identify the effect of immigration enforcement on the gender gap in inventor productivity. This identification strategy hinges on the staggered rollout of SC across counties and over time. Therefore, it is important that the timing of the rollout across counties is generally not related to time-varying county characteristics.

As discussed in Section 2.1, the SC program was rolled out on a county-by-county basis until the entire country was covered in 2013. The federal government determined the timing of each county's activation in the SC program, providing no option for counties to opt in, opt out, or forgo immigration screening. The order of rollout was solely at federal discretion, which is critical for identification. Unlike other local immigration enforcement policies, such as 287(g) agreements, local agencies had significantly less discretion in how they implemented the SC program. The literature generally concludes that the timing of this staggered rollout across counties was not related to a county's economic development or political characteristics and, in many instances, appeared quite random (Cox and Miles, 2013; East et al., 2023). Importantly, while the SC program increased the probability of deportation for undocumented immigrants, it was not designed to directly impact innovation.

4.2 Regression framework

To understand how the rollout of SC differentially impacts the productivity of male and female inventors, we use the outcome variables detailed in Section 3 to measure patenting activity at the inventor level. Following the literature (Cohn, Liu, and Wardlaw, 2022), we estimate the following fixed-effects Poisson regression model to test our hypothesis:[17]

[17] Cohn, Liu, and Wardlaw (2022) show that because count-based outcome variables often have a skewed distribution, the common practice of adding a constant to the outcome and then estimating log-linear regressions can result in

$$\text{Log}(\text{E}(Y_{i,t}|X)) = \beta_0 + \beta_1 \times SC_{i,t} + \beta_2 \times Female_i \times SC_{i,t} + \mu_i + \gamma_t + \varepsilon_{\text{i,t}}, \quad (1)$$

where $Y_{i,t}$ is one of the patent outcome measures for inventor i in year t. $SC_{i,t}$ is a dummy variable that takes the value of one if the county where the inventor resides in that year has implemented the SC program. $Female_i$ is a dummy variable that takes the value of one if the inventor is female and zero if the inventor is male. To strip out unobservable differences across inventors or years, we include a set of inventor fixed effects μ_i and year fixed effects γ_t in all our specifications.

We are interested in β_2, the coefficient of the interaction term, *Female*×*SC*. As discussed earlier in Section 2.3, women typically allocate more time to household chores and childcare than men, making them more sensitive to shifts in the availability and cost of household services. Thus, if stricter immigration enforcement policies reduce the labor supply of household services, we expect women inventors to be more adversely affected in their productivity by these enforcement measures, i.e., we expect β_2 to be negative.

4.3 Baseline results

The results are presented in Table 2. We find that the activation of SC reduced overall patenting productivity. Importantly, the negative coefficient estimates on the interaction term indicate that the effect on female inventors was significantly more negative than on male inventors.

After the rollout of SC, the number of patents filed by female inventors declined by 32% (equivalent to 0.2 patents for an average inventor); this is 24% more than the decline observed for male inventors.[18] The drop in the quality and impact of patents is 14% greater for female inventors than for male inventors when measured by total citations, with the disparity increasing to 30% when citations are scaled by the average citation count of patents filed in the same year and technology class. The effects are even more pronounced for the likelihood of producing high-

estimates that lack natural interpretation and often have incorrect signs. In contrast, Poisson regression offers desirable properties in most applications involving count or count-like data. The primary advantage of Poisson regression over log-linear regression is that it applies an exponential model to outcomes, which are likely to be approximately exponentially related to covariates, rather than transforming the data to fit a linear model.

[18] The results in Table 2 suggest that SC's reduction of undocumented immigrants had a significant negative effect on overall patenting productivity in SC-activated counties relative to non-activated counties. This finding aligns with existing literature documenting the positive influence of low-skilled immigrants on native workers' total factor productivity and R&D through labor complementarity, task specialization, and enhanced labor market competition (e.g., Borjas, 2001; Borjas, 2013; Peri, 2010; Peri, 2016). Given that our sample excludes new inventors who entered after SC's activation, this estimated effect reflects the adverse impact on existing inventors. When inventor entry is included, the overall effect of SC on patenting is not significant.

impact patents: female inventors experience a 25% greater decline in the probability of producing a top 10% cited patent compared with their male counterparts. Regarding the market value of patents, our estimates indicate that the SC program reduced the patent market value by 28% for female inventors, a 21% greater impact than for male inventors. These findings support the idea that strict enforcement from SC had an economically significant and disproportionately negative impact on female inventors.

[Table 2 about here]

5. Evidence on the Mechanism

The findings presented in Section 4 demonstrate that, following the SC rollout, female inventors experienced significantly greater declines in patenting productivity compared with male inventors. We propose an economic mechanism whereby heightened immigrant enforcement reduced the supply of undocumented immigrants in household services. This labor market shift disproportionately increased costs for female inventors to outsource household work, thereby reducing the time available for inventive activities. In this section, we provide evidence to support this proposed mechanism.

5.1 The supply of undocumented immigrant in household services

We begin by validating the effect of the SC program on the employment of likely undocumented immigrants in household services. If this stringent immigration enforcement policy indeed instilled fear among undocumented immigrant workers and reduced their labor force participation, we should expect to see a decrease in the employment of these workers in household services following the activation of SC, while employment by lawful household workers should remain largely unchanged.

To test this, we use variation in SC's implementation across counties and over time and regress the county-year employment of likely undocumented immigrants in household service occupations on the SC rollout status in a given county and year. Our baseline model includes county and year fixed effects to control for unobservable differences across states, as well as economy-wide shocks and trends. In an alternative specification, we also include county-level controls that account for local economic and labor market conditions.

We report the OLS regression results in Table 3, Panel A. As shown in columns (1) and (2), the coefficient estimates for *SC* are negative and significant at the 5% level. This finding supports our proposed economic channel, suggesting that the SC rollout was a negative shock to the employment of likely undocumented labor in household services. For instance, based on the coefficient estimate of *SC* in column (1), counties that adopted SC experienced an 8.9% reduction in the employment of likely undocumented immigrants in household services, relative to the sample mean, and a 7.9% reduction relative to the standard deviation. We find similar results when incorporating county-level controls in column (2), including the annual percentage change in county GDP and the labor force participation rate.

[Table 3 about here]

To further validate the effects of SC on the availability of household services and to rule out the possibility that lawful labor fully substituted for undocumented labor, we examine the effect of SC on lawful employment and total employment. The estimate in column (3) shows that the response of lawful employment in household services to SC adoption was statistically insignificant. Finally, the estimate in column (4) suggests a significant and negative overall effect of SC on total employment in household services, including both undocumented and lawful labor. Overall, these results provide systematic evidence that the SC program decreased the employment of likely undocumented immigrants in household services, while lawful employment remained largely unchanged.

Next, to assess whether the decreased supply of undocumented labor in household services is indeed a channel through which SC widened the gender gap in innovation, we examine how the patenting productivity of male and female inventors responded differently to changes in the supply of undocumented labor in household services. Given that this county-year labor supply is potentially endogenous to economic and technological development, we use the estimates from column (1) of Panel A in Table 3 to construct a variable, *Predicted undocumented immigrants*, which is the predicted level of employment of likely undocumented immigrants in household services. This variable has the advantage of capturing the variation of the low-skilled immigration labor in household services solely due to SC, rather than other factors. We then merge this county-year level variable into the inventor-year panel, based on each inventor's residential address each year. Our goal is to examine whether the inventor gender gap widened more in counties that experienced a greater decline in undocumented labor in household services following SC's activation.

The results are presented in Table 3, Panel B. Consistent with the baseline results in Table 2, the coefficient estimates on *Predicted undocumented immigrants* and its interaction with the *Female* dummy variable are both positive and statistically significant at the 1% level across all patenting productivity measures. Based on the coefficient estimates in column (1), a one-standard-deviation decline in the employment of likely undocumented immigrants in household services due to SC is associated with an 11.5% decline in the number of patents for male inventors, but a 14.0% decline for female inventors. Together, these results indicate that the shifts in the labor supply of undocumented immigrants in household services is an important channel through which immigrant enforcement policies exacerbate gender disparities in patenting outcomes.

To strengthen our evidence on the mechanism, we also perform a falsification test. According to our economic framework, SC's activation reduced the supply of undocumented immigrant labor in *household services*, disproportionately increasing the cost of outsourcing household tasks for female inventors. SC also affected other sectors heavily dependent on undocumented labor. For instance, according to statistics from ACS, approximately 86% of workers in agriculture are foreign-born and 45% are undocumented, while in construction, roughly 30% are immigrants, many of whom lack documentation. However, the reduced supply of undocumented labor in these industries should not differentially impact male and female inventors, making them ideal candidates for falsification analysis.

Motivated by this, we replicate the analysis in Table 3 using the employment of likely undocumented immigrants in agriculture and construction instead of household services. If our baseline findings are indeed driven by the SC-induced increase in the cost for female inventors in outsourcing household work, we should not expect to see significant effects in this falsification test. The results reported in Table IA.1 in the Internet Appendix confirm this prediction. While SC negatively impacted undocumented labor in agriculture and construction—as suggested by the significant and negative coefficient in the first stage—the coefficient estimates in the second stages are no longer significant. These falsification results provide robust support for our proposed economic mechanism.

5.2 Cross-sectional results

To provide additional evidence on the mechanism, we examine the cross-section of our sample to understand how various inventor characteristics and their work conditions moderate the observed effect of SC on the gender gap in innovation. If the effect of SC works through its impact on the availability and cost of outsourcing household tasks for female inventors, we expect the impact of SC to be more pronounced among female inventors facing greater constraints from family responsibilities, but weaker for those less susceptible to such constraints or those with stronger support.

Parenthood. In Goldin's framework that analyzes women's labor market outcomes, a major constraint on female labor supply is the need to balance family responsibilities, a demand that evolves with age (e.g., Goldin, 2014; Goldin and Katz, 2000; 2002; 2010; 2016). This burden is often heightened by childbearing and rearing, which disproportionately affects women. Consistent with this, Bertrand, Goldin, and Katz (2010) show that within-occupation gender earnings gaps emerge and widen predominantly after childbirth. Relatedly, East and Velásquez (2022) find that the SC program reduced the labor supply—specifically, hours worked—of college-educated U.S.-born mothers with young children. Building on these insights, we expect that female inventors' demand for household services, and the impact of the SC rollout on their inventive productivity, will vary with life stage, intensifying for those in the childbearing and rearing years.

To test this hypothesis, we focus on inventors likely to have young children, specifically those aged 31–45, using a dummy variable *Parenthood* to capture this information.[19] Our findings are presented in Panel A of Table 4. Among inventors outside the parenthood age range, the impact of SC on the innovation gender gap is modest. Column (1) shows that for inventors outside of parenthood age, SC reduced patenting output by 32.5% of the sample mean—equivalent to 0.2 patents—for male inventors, and by 0.22 patents for female inventors. While this difference in productivity declines between male and female inventors is statistically significant, it is economically modest. However, the difference becomes much more substantial among inventors in the parenthood years. SC reduced patenting productivity by 0.23 patents for female inventors in

[19] Our findings remain robust when we consider alternative definitions of the parenthood age interval, such as 28–48 or 25–45. Table IA.2 in the Internet Appendix contains detailed results based on specific age brackets.

parenthood, compared with 0.16 patents for their male counterparts. The positive coefficient estimates for *SC×Parenthood* suggest that being in parenthood years helped male inventors to counteract the negative impact of SC, gaining a relative "fatherhood premium," as documented in the literature (e.g., Lundberg and Rose, 2002; Glauber, 2008; Hodges and Budig, 2010). These findings indicate that the effect of SC on the gender gap in patenting productivity was heightened among those in the parenthood years. A similar pattern is observed across other patenting outcomes.

[Table 4 about here]

Inventor track record. The resilience to negative shocks may vary across inventors with different track records. Research indicates that researchers with a more successful track record exhibit greater adaptability and have better access to resources that can cushion against career disruptions (Trajtenberg, 1990; Stern, 2004; Boudreau, Ganguli, and Gaule, 2021). For example, Azoulay, Zivin, and Wang (2010) find that scholars with a stronger track record (i.e., higher past productivity) are less adversely affected by the death of a superstar coauthor. Similarly, Barber et al. (2021) find that junior scholars and Ph.D. students are significantly more vulnerable to the COVID-19 shock compared to senior faculty. Building on these findings, we expect that the negative effect of SC on the gender gap in patenting is weaker among inventors who have a better track record. To assess the empirical relevance of this idea, we create an inventor-year variable, *Track record*, calculated as the number of patents filed by (and subsequently granted to) an inventor in the past three years. Our findings in Panel B of Table 4 show that an inventor's track record significantly diminishes the effect of SC on patenting productivity gap. For example, the estimates in column (1) indicate that female inventors who filed 10 patents or more in the past three years were able to counteract the negative effect of SC on the gender gap.

Collaborative relationships. Inventors may also be less vulnerable to negative career shocks if they have strong collaborative relationships, allowing them to rely on their collaborators when facing disruptions and time constraints (Newman, 2001; Wagner and Leydesdorff, 2005; Azoulay, Zivin, and Wang, 2010). To test this idea, we construct a dummy variable, *Collaboration*, which equals one if an inventor has filed more collaborative patents in the past three years than the sample median. Panel C of Table 4 presents the results. Our findings suggest that collaborative relationships indeed significantly alleviate the negative effect of SC, especially for females. For example, the estimates in column (1) show that while strong collaborative relationships allow both female and male inventors to limit the productivity declines after the SC shock, they are especially beneficial to female inventors and can almost cancel out the effect of SC on the gender gap.

Female friendly workplace policy. To further explore the heterogeneity in the SC program's effects, we draw on insights from Goldin and Katz (2011) and Goldin (2014), who highlight workplace inflexibility as a contributing factor to the parenthood effect on gender gaps. Their findings indicate that women prefer jobs flexible enough to enable them to be the "on-call" parent. Consequently, we anticipate that workplace accommodation can also influence a woman inventor's ability to balance work with family needs. Specifically, firms that are female-friendly are more likely to provide accommodations such as flexible work arrangements, flexible work hours, maternity and adoptive leave, paid time off, and family growth support. These female-friendly policies are expected to ease the constraints faced by female inventors and mitigate the negative impact of the SC rollout.

To test this prediction, we utilize information from InHerSight ratings to evaluate the extent to which a firm is considered friendly to women employees.[20] InHerSight is the largest company reviews platform where working women can anonymously rate and review past and current employers. Users provide feedback on various factors, including salary satisfaction, paid time off, maternity and adoptive leave, and flexible work hours. Leveraging these reviews, InHerSight provides ratings for over 150,000 companies in the U.S. on their extent of female-friendliness. Among the various sub-dimensions of ratings, we focus on the ratings of policies related to flexible work hours. We define a dummy variable, *Female-friendly firm*, which takes the value of one if the InHerSight rating for the firm is in the top quartile of the rating distribution and zero otherwise. This variable indicates whether the firm is perceived as female-friendly based on its ability to provide flexible work hours.

Panel D of Table 4 presents the results. In line with the hypothesis that female-friendly firms provide workplace accommodations that better assist female inventors in balancing work with family needs and mitigating the negative impact of SC, the coefficient estimate for the triple interaction term, *SC×Female friendly firm×Female*, is positive across all patent productivity

[20] We thank Stephen Teng Sun for kindly sharing the rating data with us.

measures. For instance, the estimate in column (1) indicates that SC reduced patenting output by 0.18 patents for female inventors working for firms rated not female-friendly, but only by 0.15 for female inventors at female-friendly firms. Importantly, the estimated effect of SC on the productivity of male inventors does not vary with the firm's female-friendliness. This result suggests that flexible work accommodation policies implemented by female-friendly firms mitigate the adverse effect of SC on the gender gap in inventor productivity.

Enforcement coverage. As SC was rolled out on a county-by-county basis, undocumented immigrant labor could engage in spatial arbitrage by moving across nearby counties. However, in states where most counties adopted SC, this arbitrage potential diminishes, leading to a more pronounced reduction on the availability of household services. Thus, we anticipate a stronger effect of SC on the gender gap in inventor productivity when a higher fraction of nearby counties in the inventor's state have implemented the SC program. To test this, we introduce the variable, *State SC pass rate*, representing the fraction of counties in the inventor's residing state that have adopted SC. Results in Panel E of Table 4 show that the negative effects of SC on patenting outcomes intensified for both male and female inventors when more counties in their state implemented this policy. Crucially, the adverse impact on productivity remained more pronounced for female inventors, as reflected by the negative coefficient estimates on the triple interaction term.

5.3 Robustness checks

In this subsection, we provide a set of robustness checks and address alternative mechanisms that could potentially explain the observed link between SC rollout and innovation productivity disparities across gender.

Stacked DiD regressions. Our staggered DiD regression estimator in Eq. (1) is a variance-weighted average of several DiDs, each comparing a treated group with an effective control group that includes previously treated individuals and those not yet treated. Recent advances in econometric theory (Goodman-Bacon, 2021; Baker, Larcker, and Wang, 2021) suggest that including already-treated observations in the control group introduces bias if the treatment effect varies over time. In contrast, a stacked DiD estimator is robust to bias by using the full panel data structure, re-centering the timing of treatment for each cohort, and controlling separately for common trends within each cohort.

Following Cengiz, Arindrajit, Lindner, and Zipperer (2019) and Cronqvist, Ladika, Lindner, and Sautner (2024), we estimate a stacked DiD regression by removing already-treated inventors from the control group to identify a "clean" set of control groups. Specifically, for each of the six treatment cohorts from 2008 to 2013, we create a dataset containing inventors residing in counties that adopted SC that year (the treated) and inventors not yet affected by SC (the controls). Observations are at the inventor-year level, spanning two years before and two years after SC's activation. We then append the datasets for the six cohorts to create a "stacked" sample. Panel A of Table 5 confirms that our baseline results are robust to this specification.

[Table 5 about here]

Temporal dynamics. A key identifying assumption is that no time-varying, county-specific factor correlated with the timing of SC activation also differentially affected the patenting productivity gap between female and male inventors. This assumption is plausible because SC was targeted at the deportation of undocumented immigrants, without directly intending to influence innovation. Nevertheless, to address concerns about pre-trends, we examine the temporal dynamics of SC's effect on innovation gender gap surrounding its activation. Specifically, we estimate an augmented version of Eq (1), in which we replace the dummy variable *SC* with a set of year-specific dummies. Each dummy represents a specific year around the SC activation, ranging from two years before to four years after the SC rollout, with two years before SC's rollout as the reference year.

Panel B of Table 5 presents the results, while Figure 2 illustrates the temporal dynamics by graphically displaying the coefficient estimates of the interaction terms. As shown, no significant gender-based divergence in patenting productivity (measured by the number of patent filings) is evident prior to SC's adoption. However, following the SC rollout, the estimates turn negative and remain statistically significant at the 1% level.

The estimates also reveal an immediate effect on patenting productivity, although smaller in magnitude than the effects observed in later years. While the effect on productivity may seem rapid, it is important to note that we measure the timing of patenting by the filing date, not the grant date. As Griliches (1998) observed, in many fields, the time between R&D and patent filing is brief, often just months or weeks. Indeed, industry studies indicate that R&D project durations average under 12 months for semiconductors, 3 to 6 months for information and communication technologies, and even shorter for software (Griss 1993; Wu, 2011; Kapoor 2012). In addition, there is evidence that in some cases, patents are filed at early R&D stages rather than at completion (Cohen 2010).

Alternative model specifications. First, because our sample period spans the Great Recession, we test the robustness of the results by accounting for county-level time-varying economic conditions that may influence patenting outcomes. Specifically, we include county and year fixed effects, as well as county-by-year fixed effects. Additionally, state-level economic fluctuations may affect the intensity and quality of innovation, and the Great Recession may have had a differential impact on highly-educated women. To control for these factors, we conduct robustness tests by including state-by-year fixed effects or gender-by-year fixed effects—alongside invention and year fixed effects—and our results remain robust.

Second, we perform inventor-level regressions similar to those in Bernstein et al. (2021), in which we construct two outcome variables for each inventor: one for the sum of the inventor's patenting outcomes in years [+1, +5] after SC's rollout, and the other for the sum of the patenting outcomes in years [-5, -1] prior to SC's rollout. The variable *Post* is a dummy that takes the value of one for outcomes [+1, +5] and zero for [-5, -1]. Finally, instead of Poisson, we also run OLS regressions using the log of one plus the patenting outcomes to reduce the effects of outliers. As shown in Panel A of Table 6, our results are robust across all these alternative specifications.

[Table 6 about here]

Alternative patenting outcome measures. We also consider alternative measures of patenting outcomes. To account for the effect of team collaboration on the productivity of an individual inventor, we use two measures: the fraction of solo-inventor patents and the weighted number of patents with each patent's weight equal to one divided by the total number of inventors on the patent. To gauge the breadth of the patents, we calculate the number of technology fields covered by an inventor's patents. As additional robustness checks, we also examine the number of top 5% cited patents, and the market value of the average patent. Panel B of Table 6 shows that our results are robust to all these alternative measures.

Inventor attrition. In addition to the various patenting outcomes discussed above, we also examine the effect of SC adoption on inventor attrition. Specifically, we track male and female inventors over time to assess SC's impact on what is commonly termed "leaving science." Following approaches in the literature (e.g., Kwiek and Szymula 2024), we identify an attrition event as an inventor ceasing to patent for a prolonged period (alternatively defined as three, four, or five subsequent years). Using logit regressions, we find that SC's passage is significantly associated with an increased likelihood of inventor attrition, with the effect notably stronger for female inventors. These findings suggest that immigration enforcement policies may widen the gender gap in innovation by affecting not only immediate productivity but also long-term career retention, leading to a complete exit for some inventors from the field.

Local immigration enforcement policies. To address the concern that our estimates may inadvertently capture the effects of other local immigration enforcement policies implemented around the same time as SC, such as the optional 287(g) agreements, we control for the presence of these agreements over time by counties. The 287(g) agreements authorized local law enforcement to act as immigration agents, including checking immigration status among individuals who were arrested. These agreements share similarities in design with SC and could potentially affect the labor supply of undocumented immigrants, subsequently influencing the gender gap in innovation. We obtain the start and end dates for all 287(g) agreements from multiple sources, including reports published by ICE, the Department of Homeland Security, the Migration Policy Institute, Kostandini, Mykerezi, and Escalante (2014), and news articles.

In Panel C of Table 6, our findings indicate that controlling for the optional 287(g) agreements does not diminish the observed impact of SC on the gender gap in innovation. One possible explanation is that the adoption of 287(g) agreements was voluntary and limited to only about 50 counties. Moreover, the adoption itself could be endogenous to local conditions (Bohn and Santillano, 2017; Pham and Van, 2010). This suggests that the effect of SC on the gender gap in innovation was distinct from the impact of the 287(g) agreements.

Alternative subsamples. We also conduct robustness checks with subsamples, with results shown in Panel D of Table 6. Given that some of the earliest activations of SC were shown to be related to the fraction of the county's Hispanic population, the county's distance from the U.S.-Mexico border, and the presence of local 287(g) agreements, we exclude those early adopter counties (i.e., counties that adopted SC in 2008), and the results are virtually unchanged. Similarly, we also conduct a robustness test by excluding all counties along the Mexican border. Our findings remain robust, suggesting that the observed effect is broad-based across the country.

Second, our primary analysis relies on inventor gender information obtained from PatentsView. To predict gender based on each inventor's name, the algorithm uses country-specific lists that assign approximate probabilities to each gender for names within that country. However, accurately determining gender can be challenging for certain names, especially Asian ones. We conduct a robustness test by excluding inventors identified with Asian names, and our results remain unchanged.[21]

Finally, a possibility is that the impact of Secure Communities on innovative activities operates through disproportionate effects on Hispanic inventors. Immigrants from Latin American countries, particularly Hispanics individuals, were overrepresented among those deported under the SC program. Statistics reveal that that 90% of deportations were Hispanic, with 63% being Mexican.[22] Prior research suggests that SC had a disproportionate impact on Hispanic households. For instance, Wang and Kaushal (2019) find that exposure to immigration enforcement policies, including SC, increases mental distress among Latino immigrants. Additionally, Alsan and Yang (2022) show that SC reduces the participation of eligible Hispanic citizens in safety net programs. Advocacy groups have suggested that SC provides a means for law enforcement to target the Hispanic population by using minor violations (Kohli, Markowitz, and Chavez, 2011). To investigate this issue, we re-estimate the model focusing exclusively on non-Hispanic inventors. The race and ethnicity of an inventor is predicted using the ethnicolr algorithm, which provides

[21] To impute race and ethnicity we use Ethnicolr, a machine-learning-based classifier trained on a specific data set and implemented in Python (Laohaprapanon and Sood 2017). This algorithm assigns persons based on their first and last names to four categories that combine race and ethnicity, specifically Hispanic (regardless of race), non-Hispanic White, non-Hispanic Black, and non-Hispanic Asian. In this robustness check, we exclude all inventors assigned a probability of 50% or higher for non-Hispanic Asian names, which represent about 10% of our sample.
[22] These statistics on removals under SC come from the Transactional Records Access Clearinghouse (TRAC), as reported in East et al (2023).

the most likely ethnicities with associated probabilities. We classify a person's ethnicity as Hispanic only if ethnicolr can provide Hispanic ethnicity information with a probability of accuracy exceeding 50 percent. Our findings remain robust and equally strong among the subsample of non-Hispanic inventors, suggesting that our baseline results are not solely driven by the effects of the SC program on Hispanic inventors.

6. Conclusion

This paper examines the effect of immigration enforcement policies on the gender gap in innovation. We leverage the staggered rollout of the Secure Communities (SC) program from 2008 to 2013—a large-scale immigration enforcement initiative that heightened the risk of deportation for undocumented immigrants. Our analysis of inventor-level data reveals that female inventors experienced significantly greater declines in patenting outcomes than their male counterparts following the SC rollout. These declines are evident across various measures, including the quantity, quality, and market value of patents. We provide evidence that the SC program reduced the supply of undocumented immigrant labor in household services, thereby disproportionately raising the cost of outsourcing household tasks for female inventors. This, in turn, reduced the time they could dedicate to inventive activities. Consistent with this mechanism, we find that the more substantial negative impact on female inventors is particularly pronounced for those likely to have young children but is less severe for inventors with a successful track record, with access to collaborators, or employed by more female-friendly firms.

Our study highlights a significant unintended consequence of immigration enforcement policies: these policies, by altering the availability of household services provided by low-skilled undocumented immigrants, disproportionately affect the time allocation and productivity of high-skilled female inventors. More broadly, policies that impact the labor market supply of low-skilled immigrants can have cascading effects on high-skilled inventors, potentially exacerbating the gender productivity gap within this group. These findings underscore the crucial role that household services play in supporting the productivity of female inventors, suggesting that improving the availability and affordability of these services could be a key strategy in addressing gender disparities in inventive activities.

Appendix A: Variable Definitions

Variable name	Description
<u>*Measures of innovation productivity*</u>	
Total patents	The number of patents filed by (and subsequently granted) to an inventor in a given year.
Citations	The number of citations received by all the patents filed by (and subsequently granted to) an inventor in a given year.
Scaled citations	The number of citations received by all the patents filed by (and subsequently granted to) an inventor in a given year, scaled by the average number of citations received by patents filed in the same year and CPC technology sub-class.
Citations per patent	The average number of citations received by each patent filed by (and subsequently granted to) an inventor in a given year.
Scaled citations per patent	The average number of citations received by each patent filed by (and subsequently granted to) an inventor in a given year, scaled by the average number of citations received by patents filed in the same year and CPC technology sub-class.
Top 10% cited patents	The number of patents that are classed as a top 10% cited patent (i.e., one that receives citations from other patents that place the focal patent in the top 10% of patents in the same application year and CPC technology sub-class).
Top 5% cited patents	The number of patents that are classed as a top 5% cited patent (i.e., one that receives citations from other patents that place the focal patent in the top 5% of patents in the same application year and CPC technology sub-class).
Patent market value	The total real market value of an inventor's patents that are assigned to public traded firms in a given year.
Market value per patent	The average real market value of an inventor's patents that are assigned to public traded firms in a given year.
Frac solo-inventor patent	The fraction of solo-inventor patents for an inventor who filed (and was subsequently granted) at least one patent in a given year.
Weighted patent	The weighted number of patents filed by (and subsequently granted to) an inventor in a given year, where each patent's weight is defined as 1 divided by the total number of inventors on the patent.
Number of fields	The number of WIPO technology fields into which patents filed by (and subsequently granted to) an inventor in a given year are classified.
Inventor attrition	A dummy variable that takes the value of one if the inventor has zero patent filed (and subsequently granted) between year t and $t+i$, where i takes the value of 3, 4 or 5; otherwise, it is coded as 0. Year t is between 2006 to 2015.
<u>*Other variables*</u>	
Female	A dummy variable that takes the value of one if the inventor is female and zero otherwise.

SC	A dummy variable that takes the value of one if the county where the inventor resides that year has implemented the SC program. The data is publicly available from ICE https://www.ice.gov/foia/identiafis-interoperability-monthly-statistics-through-dec-2014.
State SC pass rate	The fraction of counties in a state that have implemented the SC program in a given year in which the inventor resides that year.
Employment of likely undocumented immigrants in household services	The annual hours worked in private households (Occupations: 399021-Personal Care Aides; 372012-Maids and Housekeeping Cleaners; 399011-Childcare Workers) by likely undocumented immigrants in each county-year, divided by the county's population in 2005. We follow the literature (e.g., East et al. 2022, Bansak and Pearlman (2021), Mockus and Jung 2022) and identify likely undocumented immigrants as foreign-born individuals with less than a high school degree from the American Community Survey (ACS).
Lawful employment in household services	The annual hours worked in private households under likely lawful employment in each county-year, divided by the county's population in 2005. We identify likely lawful employment by total employed labor minus likely undocumented immigrants (foreign-born individuals with less than a high school degree from the ACS).
Total employment in household services	The annual hours worked in private households in each county-year, divided by the county's population in 2005.
Parenthood	A dummy variable that takes the value of one if the inventor is at childbearing and rearing age (between 31 and 45 years old) and zero otherwise. The source is Kaltenberg, Jaffe, and Lachman (202) "Matched inventor ages from patents, based on web scraped sources", https://doi.org/10.7910/DVN/YRLSKU, Harvard Dataverse, V1
Collaboration	A dummy variable that takes the value of one for an inventor-year if the number of patents filed (and subsequently granted) in collaboration with others by the inventor over the past three years is above the annual sample median for that year.
Track record	The number of patents filed by (and subsequently granted) to an inventor in the past three years.
Female friendly firm	A dummy variable that takes the value of one if the firm's InHerSight ratings are in the top quartile of the distribution and zero otherwise. The ratings are obtained from InHerSight.com, which is platform for posting anonymous employer ratings and reviews by working women. Users give feedback according to the following factors such as salary satisfaction, paid time off, maternity and adoptive leave, and flexible work hours. We focus on the ratings based on the flexible work hours to proxy for the women-friendliness of the company's workplace.
g(287)	A dummy variable that takes the value of one if the county has a 287(g) agreement in place that year.

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Figure 1. The Staggered Rollout of the Secure Communities Program

The Secure Communities program was rolled out on a county-by-county basis between October 27, 2008 and January 22, 2013. The counties in darker shades activated the SC program earlier than counties in lighter shades.

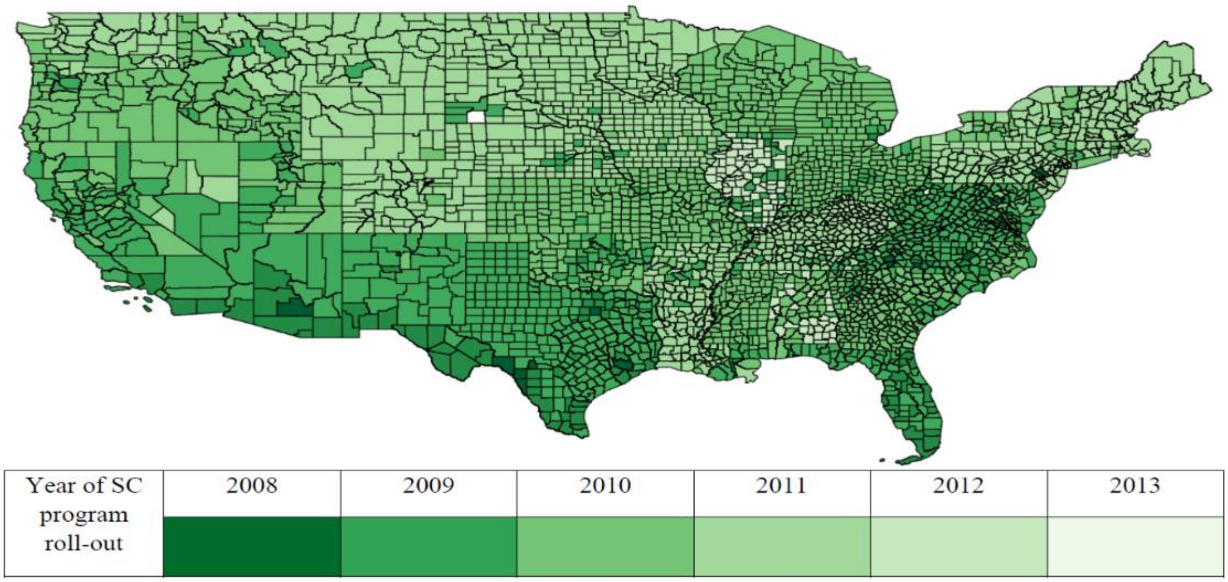

Figure 2. The Effect of SC on Gender Gap in Innovation Year by Year

This figure plots the point estimates of $\beta_{2,t}$ in the following regression:

$$\mathrm{Log}(\mathrm{E}(Y_{i,t}|X)) = \beta_0 + \sum_{t=-1}^{4} \beta_{1,t} \ + \ \sum_{t=-1}^{4} \beta_{2,t} \times Female_i \ + \ \mu_i + \gamma_t + \varepsilon_{\mathrm{i,t}},$$

where the outcome variable is *Total patents*, filed by (and subsequently granted) to an inventor in a given year. This is an augmented version of Eq (1), in which we replace the dummy variable *SC* with a series of year-specific dummy variables, each representing a particular year around SC's adoption. The sample is restricted to two years before, to four years after SC's rollout. We set the period two years before the SC rollout as the reference year, omitting the interaction term for this period. The vertical bars correspond to the 95% confidence intervals based on standard errors clustered by county.

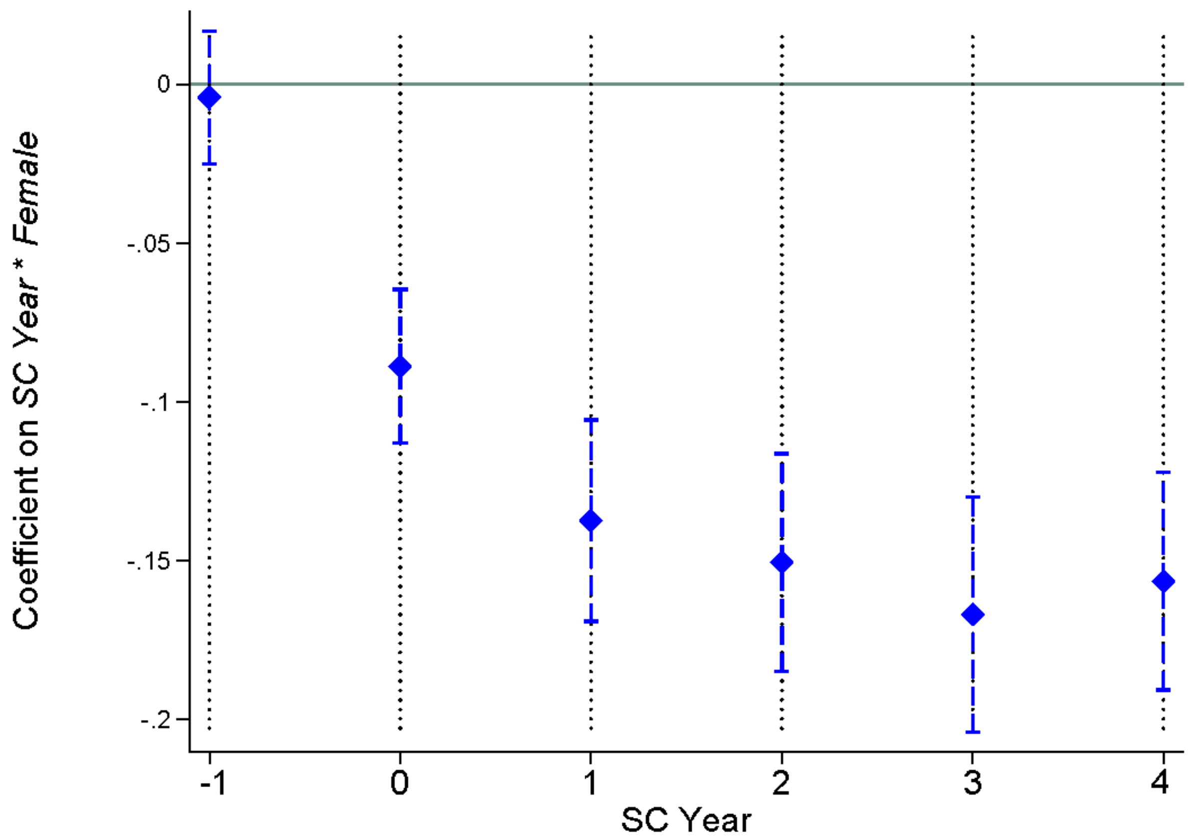

Table 1. Summary statistics of main variables

This table reports the summary statistics for our main sample of inventor-year observations, covering 319,269 unique inventors and 972,249 unique patents. Definitions of all variables are provided in Appendix A.

Variable	N	Mean	Median	SD	P10	P90
Total patents	3,192,690	0.609	0	1.246	0	2
Citations	3,192,690	4.493	0	16.66	0	10
Scaled citations	3,192,690	0.734	0	2.505	0	1.696
Citations per patent	3,192,690	2.190	0	7.257	0	6
Scaled citations per patent	3,192,690	0.346	0	1.029	0	0.987
Top 10% cited patents	3,192,690	0.095	0	0.359	0	0
Patent market value	2,670,452	4.127	0	14.85	0	9.403
Female	3,192,690	0.121	0	0.326	0	1
SC	3,192,690	0.547	1	0.498	0	1
Frac solo-inventor patent	3,192,690	0.047	0	0.198	0	0
Weighted patent	3,192,690	0.238	0	0.528	0	0.833
Number of fields	3,192,690	0.605	0	1.049	0	2
Top 5% cited patents	3,192,690	0.046	0	0.234	0	0
Market value per patent	2,670,452	2.037	0	6.717	0	5.783
Inventor attrition	3,192,690	0.339	0	0.473	0	1
Parenthood	2,646,750	0.44	1	0.496	0	1
Collaboration	3,192,690	0.356	0	0.479	0	1
Track record	3,192,690	1.776	1	2.947	0	5
Female friendly firm	696,590	0.252	0	0.434	0	1
State SC pass rate	3,192,690	0.406	0.048	0.471	0	1
g(287)	3,192,690	0.119	0	0.323	0	1

Table 2. Rollout of Secure Communities and the gender gap in patenting productivity

This table reports Poisson regression estimates of the relation between the rollout of the SC program and the patenting productivity gaps between male and female inventors. The outcome variable is one of the patenting outcome measures for an inventor in a given year. *Female* is a dummy variable that takes the value of one if the inventor is female and zero otherwise. *SC* is a dummy variable that takes the value of one if the county where the inventor resides that year has implemented the SC program. To strip out unobservable differences across inventors or years, we include a set of inventor fixed effects and year fixed effects in all specifications. Standard errors clustered at the inventor level are reported in parentheses below each point estimate. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Definitions of all variables are provided in Appendix A.

	Quantity	Quality					Value
	Total patents	Citations	Scaled citations	Citations per patent	Scaled citations per patent	Top 10% cited patents	Market value
SC	-0.303***	-0.307***	-0.246***	-0.457***	-0.381***	-0.224***	-0.259***
	(0.020)	(0.022)	(0.020)	(0.021)	(0.018)	(0.020)	(0.042)
SC × *Female*	-0.088***	-0.052***	-0.086***	-0.069***	-0.114***	-0.065***	-0.065**
	(0.013)	(0.018)	(0.018)	(0.018)	(0.016)	(0.020)	(0.026)
Constant	-0.080***	3.093***	0.735***	2.063***	-0.325***	-1.097***	2.671***
	(0.015)	(0.014)	(0.015)	(0.014)	(0.017)	(0.016)	(0.035)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,190,870	2,863,950	2,863,800	2,863,950	2,863,800	1,140,200	1,640,320

Table 3. The economic channel: Undocumented labor supply in household services

This table presents evidence on the economic channel based on two analyses. Panel A reports the first analysis, which validates SC's negative effect on the supply of undocumented immigration labor in household services. We regress the employment of likely undocumented immigrants in household services in a county-year on the rollout status of SC in that county for that year, controlling for county and year fixed effects. In the second analysis, we assess whether the supply of undocumented immigrant labor in household services is indeed the mechanism through which SC widened gender gap in invention. We obtain from the first analysis the predicted values of employment of likely undocumented immigrants in household service—variable *Predicted undocumented immigrants* for each county-year—and map it to the inventor-level sample according to each inventor's residential address each year. We then perform Poisson regression and report the results in panel B. Outcome variable takes the value of one of the innovation outcome measures for an inventor in a given year. *Female* is a dummy variable that takes the value of one if the inventor is female and zero otherwise. Standard errors clustered at the inventor level are reported in parentheses below each point estimate. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Definitions of all variables are provided in Appendix A.

Panel A: Rollout of Secure Communities and the employment of likely undocumented immigrants in household services

	Annual hours worked in private households			
	Likely undocumented immigrants		Lawful employment	Total employment
	(1)	(2)	(3)	(4)
SC	-0.209**	-0.196**	-0.542	-0.654*
	(0.103)	(0.097)	(0.338)	(0.344)
Constant	2.286***	2.321***	15.58***	17.15***
	(0.072)	(0.080)	(0.230)	(0.241)
County-level controls	No	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,449	2,439	3,574	3,574
R-squared	0.832	0.833	0.589	0.677

Panel B. Undocumented labor supply and the gender gap in patenting productivity

	Quantity	Quality					Value
	Total patents	Citations	Scaled citations	Citations per patent	Scaled citations per patent	Top 10% cited patents	Market value
Female×Predicted undocumented immigrants	0.333***	0.577***	0.353***	0.585***	0.385***	0.305***	0.320**
	(0.105)	(0.098)	(0.104)	(0.091)	(0.104)	(0.113)	(0.134)
Predicted undocumented immigrants	1.416***	1.351***	1.120***	2.091***	1.815***	1.027***	1.249***
	(0.149)	(0.139)	(0.135)	(0.150)	(0.140)	(0.132)	(0.290)
Constant	-3.336***	-0.054	-1.834***	-2.790***	-4.503***	-3.442***	-0.206
	(0.359)	(0.320)	(0.323)	(0.343)	(0.332)	(0.315)	(0.692)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,975,708	1,776,461	1,776,402	1,776,461	1,776,402	715,306	1,066,916

Table 4. The economic channel: cross-sectional evidence

This table reports Poisson regression estimates of the relation between the rollout of the SC program and the patenting productivity gap across male and female inventors, interacted with various inventor-level or county-level characteristics. In Panel A, we introduce a dummy variable, *Parenthood*, which takes the value of one if the inventor is at child-bearing and rearing age (age is between 31 and 45 years) and zero otherwise. In Panel B, *Track record* is calculated as the number of patents filed by (and subsequently granted to) an inventor in the past three years. In Panel C, we construct a dummy variable, *Collaboration*, which equals one if an inventor has filed more collaborative patents in the past three years than the sample median. In Panel D, *Female friendly firm*, takes the value of one if the distribution of the InHerSight ratings of the firm is in the top quartile and zero otherwise. In Panel E, we introduce a continuous variable *State SC pass rate*, which is the fraction of counties that have implemented the SC program in a state in a year where the inventor resides that year. Standard errors clustered at the inventor level are reported in parentheses below each point estimate. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Definitions of all variables are provided in Appendix A.

Panel A: Cross-sectional evidence—the role of parenthood

	Quantity	Quality					Value
	Total patents	Citations	Scaled citations	Citations per patent	Scaled citations per patent	Top 10% cited patents	Market value
SC	-0.393***	-0.400***	-0.336***	-0.542***	-0.467***	-0.313***	-0.353***
	(0.022)	(0.025)	(0.022)	(0.025)	(0.021)	(0.021)	(0.044)
SC×Female	-0.046**	0.009	-0.039	-0.034	-0.087***	-0.009	-0.013
	(0.018)	(0.032)	(0.031)	(0.026)	(0.023)	(0.031)	(0.037)
SC×Parenthood	0.079***	0.068***	0.065***	0.059***	0.063***	0.066***	0.069***
	(0.009)	(0.015)	(0.015)	(0.013)	(0.012)	(0.014)	(0.019)
SC×Parenthood ×Female	-0.107***	-0.147***	-0.136***	-0.104***	-0.102***	-0.149***	-0.108***
	(0.018)	(0.046)	(0.046)	(0.034)	(0.033)	(0.040)	(0.036)
Parenthood ×Female	0.065***	0.081**	0.098***	0.059*	0.068**	0.099***	0.082**
	(0.018)	(0.036)	(0.036)	(0.031)	(0.029)	(0.034)	(0.034)
Parenthood	0.099***	0.114***	0.119***	0.081***	0.079***	0.111***	0.138***
	(0.013)	(0.015)	(0.016)	(0.011)	(0.012)	(0.015)	(0.030)
Constant	-0.250***	2.903***	0.546***	1.941***	-0.435***	-1.230***	2.512***
	(0.017)	(0.017)	(0.018)	(0.016)	(0.019)	(0.018)	(0.043)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,645,220	2,366,640	2,366,510	2,366,640	2,366,510	882,300	1,332,110

Panel B: Cross-sectional evidence—the role of track record

	Quantity	Quality					Value
	Total patents	Citations	Scaled citations	Citations per patent	Scaled citations per patent	Top 10% cited patents	Market value
SC	-0.420***	-0.412***	-0.318***	-0.589***	-0.506***	-0.284***	-0.315***
	(0.022)	(0.023)	(0.020)	(0.022)	(0.019)	(0.020)	(0.038)
SC×Female	-0.119***	-0.073***	-0.132***	-0.095***	-0.154***	-0.102***	-0.116***
	(0.016)	(0.024)	(0.023)	(0.022)	(0.021)	(0.027)	(0.035)
SC× Track record	0.021***	0.018***	0.012***	0.034***	0.032***	0.010***	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
SC× Track record ×Female	0.011***	0.008***	0.009***	0.019***	0.020***	0.008**	0.018***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)
Track record ×Female	-0.005***	-0.001	0.002	-0.012***	-0.007*	0.000	-0.009***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)
Track record	0.014***	-0.007***	0.013***	-0.031***	-0.014***	0.014***	0.022***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Constant	-0.127***	3.116***	0.688***	2.138***	-0.294***	-1.143***	2.599***
	(0.015)	(0.016)	(0.016)	(0.016)	(0.018)	(0.017)	(0.036)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,190,870	2,863,950	2,863,800	2,863,950	2,863,800	1,140,200	1,640,320

Panel C: Cross-sectional evidence—the role of collaborative relationships

	Quantity	Quality					Value
	Total patents	Citations	Scaled citations	Citations per patent	Scaled citations per patent	Top 10% cited patents	Market value
SC	-0.501***	-0.450***	-0.365***	-0.669***	-0.571***	-0.322***	-0.373***
	(0.023)	(0.028)	(0.024)	(0.026)	(0.022)	(0.023)	(0.039)
SC×Female	-0.151***	-0.118***	-0.152***	-0.112***	-0.154***	-0.140***	-0.178***
	(0.018)	(0.033)	(0.033)	(0.030)	(0.028)	(0.038)	(0.035)
SC×Collaboration	0.288***	0.202***	0.166***	0.356***	0.325***	0.138***	0.147***
	(0.020)	(0.024)	(0.025)	(0.022)	(0.021)	(0.025)	(0.040)
SC×Collaboration ×Female	0.129***	0.127***	0.116***	0.125***	0.113***	0.123***	0.205***
	(0.016)	(0.034)	(0.036)	(0.031)	(0.031)	(0.043)	(0.032)
Collaboration ×Female	-0.084***	-0.087***	-0.056**	-0.095***	-0.070***	-0.048	-0.158***
	(0.014)	(0.026)	(0.028)	(0.022)	(0.022)	(0.036)	(0.028)
Collaboration	-0.075***	-0.169***	-0.037**	-0.345***	-0.220***	-0.029	0.041*
	(0.018)	(0.020)	(0.019)	(0.019)	(0.018)	(0.018)	(0.024)
Constant	-0.036*	3.194***	0.757***	2.236***	-0.218***	-1.079***	2.655***
	(0.020)	(0.020)	(0.020)	(0.019)	(0.021)	(0.021)	(0.044)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,190,870	2,863,950	2,863,800	2,863,950	2,863,800	1,140,200	1,640,320

Panel D: Cross-sectional evidence—the role of female friendly workplace policy

	Quantity	Quality					Value
	Total patents	Citations	Scaled citations	Citations per patent	Scaled citations per patent	Top 10% cited patents	Market value
SC	-0.219***	-0.269***	-0.173***	-0.424***	-0.315***	-0.167***	-0.212***
	(0.027)	(0.043)	(0.033)	(0.041)	(0.031)	(0.035)	(0.037)
SC×Female	-0.120***	-0.122***	-0.154***	-0.108***	-0.151***	-0.132***	-0.115***
	(0.025)	(0.039)	(0.037)	(0.035)	(0.029)	(0.041)	(0.039)
SC×Female friendly firm	-0.006	0.081	0.051	0.093	0.055	0.032	-0.083
	(0.036)	(0.058)	(0.056)	(0.060)	(0.058)	(0.056)	(0.070)
SC×Female friendly firm×Female	0.063*	0.164**	0.141*	0.117*	0.110	0.129*	0.176***
	(0.038)	(0.072)	(0.078)	(0.069)	(0.071)	(0.076)	(0.055)
Constant	0.031	3.229***	0.858***	2.163***	-0.249***	-1.043***	2.825***
	(0.026)	(0.024)	(0.030)	(0.021)	(0.027)	(0.030)	(0.045)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	696,340	630,210	630,200	630,210	630,200	282,500	578,060

Panel E: Cross-sectional evidence—the role of SC enforcement

	Quantity	Quality					Value
	Total patents	Citations	Scaled citations	Citations per patent	Scaled citations per patent	Top 10% cited patents	Market value
SC	-0.265***	-0.267***	-0.213***	-0.406***	-0.339***	-0.197***	-0.226***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.017)	(0.020)	(0.044)
SC×Female	-0.038***	-0.016	-0.028	-0.021	-0.041**	-0.035	-0.034
	(0.013)	(0.019)	(0.019)	(0.020)	(0.020)	(0.022)	(0.026)
SC×State SC pass rate	-0.608***	-0.504***	-0.540***	-0.573***	-0.563***	-0.350*	-0.384
	(0.151)	(0.144)	(0.138)	(0.165)	(0.170)	(0.190)	(0.287)
SC×State SC pass rate×Female	-0.838***	-1.113***	-0.720**	-1.028***	-0.741***	-0.149	-0.935***
	(0.219)	(0.292)	(0.298)	(0.305)	(0.236)	(0.305)	(0.275)
State SC pass rate×Female	0.776***	1.059***	0.644**	0.949***	0.639***	0.108	0.898***
	(0.218)	(0.289)	(0.296)	(0.304)	(0.233)	(0.301)	(0.275)
State SC pass rate	0.385**	0.232	0.318**	0.203	0.247	0.153	0.176
	(0.162)	(0.158)	(0.148)	(0.181)	(0.180)	(0.201)	(0.305)
Constant	-0.081***	3.092***	0.734***	2.061***	-0.326***	-1.097***	2.670***
	(0.014)	(0.015)	(0.015)	(0.015)	(0.017)	(0.016)	(0.035)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,190,870	2,863,950	2,863,800	2,863,950	2,863,800	1,140,200	1,640,320

Table 5. Robustness checks on identification

This table reports the robustness checks of the baseline results. In Panel A, we report the results of stacked difference-in-differences. In Panel B, we report the temporal dynamics of SC's effect on the innovation gender gap surrounding its adoption, with patenting productivity measured as the number of patents filed (and subsequently granted). Specifically, we estimate an augmented version of Eq (1), in which we replace the dummy variable SC with a series of year-specific dummy variables, each representing a particular year around SC's adoption. The sample is restricted to two years before, to four years after SC's rollout. We set the period two years before the SC rollout as the reference year, omitting the interaction term for this period. Standard errors clustered at the inventor level are reported in parentheses below each point estimate. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Definitions of all variables are provided in Appendix A.

Panel A: stacked difference-in-differences

	Quantity	Quality					Value
	Total patents	Citations	Scaled citations	Citations per patent	Scaled citations per patent	Top 10% cited patents	Market value
SC	-0.407***	-0.365***	-0.350***	-0.514***	-0.495***	-0.343***	-0.404***
	(0.025)	(0.026)	(0.023)	(0.025)	(0.022)	(0.024)	(0.059)
SC×Female	-0.100***	-0.074***	-0.087***	-0.085***	-0.105***	-0.076***	-0.101***
	(0.012)	(0.015)	(0.016)	(0.015)	(0.016)	(0.018)	(0.024)
Constant	0.252***	3.015***	1.058***	2.085***	0.118***	-0.606***	2.958***
	(0.008)	(0.006)	(0.007)	(0.005)	(0.006)	(0.007)	(0.019)
Cohort-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort-by-inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,295,880	4,563,350	4,563,110	4,563,350	4,563,110	1,477,375	2,501,379

Panel B: Temporal dynamics

	Quantity	Quality					Value
	Total patents	Citations	Scaled citations	Citations per patent	Scaled citations per patent	Top 10% cited patents	Market value
Before1	0.044***	-0.165***	0.025*	-0.190***	0.000	0.049***	0.053***
	(0.012)	(0.015)	(0.015)	(0.011)	(0.011)	(0.014)	(0.017)
Female×Before1	-0.004	-0.001	0.005	0.003	0.008	0.011	-0.010
	(0.011)	(0.020)	(0.019)	(0.021)	(0.019)	(0.023)	(0.019)
Year0	-0.144***	-0.520***	-0.146***	-0.631***	-0.261***	-0.089***	-0.132***
	(0.018)	(0.019)	(0.016)	(0.017)	(0.016)	(0.019)	(0.024)
After1	-0.273***	-0.852***	-0.285***	-1.049***	-0.488***	-0.198***	-0.260***
	(0.017)	(0.021)	(0.015)	(0.018)	(0.013)	(0.019)	(0.023)
After2	-0.282***	-1.087***	-0.325***	-1.293***	-0.543***	-0.203***	-0.263***
	(0.017)	(0.023)	(0.015)	(0.018)	(0.013)	(0.022)	(0.028)
After3	-0.304***	-1.343***	-0.390***	-1.579***	-0.641***	-0.252***	-0.309***
	(0.017)	(0.031)	(0.016)	(0.026)	(0.013)	(0.027)	(0.031)
After4	-0.335***	-1.575***	-0.411***	-1.848***	-0.700***	-0.261***	-0.382***
	(0.022)	(0.045)	(0.022)	(0.038)	(0.018)	(0.034)	(0.030)
Female×Year0	-0.089***	-0.064***	-0.064***	-0.073***	-0.080***	-0.066***	-0.099***
	(0.012)	(0.022)	(0.023)	(0.023)	(0.024)	(0.025)	(0.034)
Female×After1	-0.137***	-0.147***	-0.145***	-0.153***	-0.161***	-0.120***	-0.137***
	(0.016)	(0.025)	(0.025)	(0.027)	(0.026)	(0.029)	(0.033)
Female×After2	-0.150***	-0.100***	-0.120***	-0.121***	-0.142***	-0.071***	-0.138***
	(0.017)	(0.027)	(0.024)	(0.024)	(0.023)	(0.027)	(0.032)
Female×After3	-0.167***	-0.180***	-0.175***	-0.217***	-0.220***	-0.174***	-0.162***
	(0.019)	(0.029)	(0.029)	(0.029)	(0.027)	(0.032)	(0.038)
Female×After4	-0.156***	-0.166***	-0.161***	-0.203***	-0.214***	-0.119***	-0.129***
	(0.017)	(0.038)	(0.036)	(0.032)	(0.031)	(0.037)	(0.044)
Constant	0.367***	3.082***	1.152***	2.120***	0.170***	-0.566***	3.186***
	(0.019)	(0.036)	(0.011)	(0.029)	(0.009)	(0.030)	(0.025)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,956,433	1,688,980	1,688,889	1,688,980	1,688,889	617,142	970,844

Table 6. Robustness tests

This table reports the robustness checks of the baseline results. In Panel A, we show our results are robust across alternative specifications, including various fixed effects specifications, inventor-level regressions similar to those in Bernstein et al. (2021), and OLS regressions using the log of one plus the patenting outcomes to reduce the effects of outliers. Panel B reports the results using alternative measures of patenting outcomes. In Panel C, we control for the optional 287(g) agreements. We obtain the start and end dates for all 287(g) agreements 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. In Panel D, we report robust results across various subsamples: (i) when excluding early adopters of SC program; (ii) when excluding inventors with Asian names; (iii) when excluding inventions with Hispanic ethnicity; (iv) when excluding the counties on the Mexico-United States border. Standard errors clustered at the inventor level are reported in parentheses below each point estimate. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Definitions of all variables are provided in Appendix A.

Panel A: Alternative model specifications

	Quantity	Quality					Value
	Total patents	Citations	Scaled citations	Citations per patent	Scaled citations per patent	Top 10% cited patents	Market value
Including county and year fixed effects							
SC	-0.304***	-0.309***	-0.248***	-0.458***	-0.382***	-0.225***	-0.259***
	(0.020)	(0.022)	(0.020)	(0.021)	(0.018)	(0.020)	(0.042)
SC×Female	-0.074***	-0.036*	-0.069***	-0.060***	-0.102***	-0.057***	-0.063**
	(0.013)	(0.020)	(0.020)	(0.019)	(0.019)	(0.021)	(0.029)
Female	-0.244***	-0.374***	-0.393***	-0.271***	-0.297***	-0.393***	-0.108***
	(0.011)	(0.023)	(0.026)	(0.017)	(0.020)	(0.025)	(0.029)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,192,690	3,191,860	3,191,860	3,191,860	3,191,860	3,174,190	3,169,480
Including county-by-year fixed effects							
SC×Female	-0.088***	-0.047***	-0.078***	-0.072***	-0.111***	-0.069***	-0.085***
	(0.012)	(0.018)	(0.018)	(0.017)	(0.016)	(0.019)	(0.028)
Female	-0.237***	-0.371***	-0.388***	-0.268***	-0.293***	-0.386***	-0.096***
	(0.010)	(0.022)	(0.025)	(0.017)	(0.019)	(0.024)	(0.030)
County-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,192,690	3,191,860	3,191,860	3,191,860	3,191,860	3,174,190	3,169,480

Including inventor fixed effects, year fixed effects, and state-by-year fixed effects							
SC	-0.233***	-0.233***	-0.201***	-0.343***	-0.294***	-0.184***	-0.216***
	(0.032)	(0.028)	(0.028)	(0.028)	(0.026)	(0.028)	(0.036)
SC×Female	-0.096***	-0.061***	-0.091***	-0.079***	-0.119***	-0.075***	-0.081***
	(0.011)	(0.016)	(0.016)	(0.015)	(0.014)	(0.017)	(0.021)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,190,770	2,863,842	2,863,692	2,863,842	2,863,692	1,139,996	1,640,142
Including inventor fixed effects, year fixed effects, and gender-by-year fixed effects							
SC	-0.296***	-0.297***	-0.242***	-0.447***	-0.377***	-0.220***	-0.244***
	(0.020)	(0.021)	(0.020)	(0.020)	(0.018)	(0.020)	(0.044)
SC×Female	-0.154***	-0.163***	-0.129***	-0.175***	-0.155***	-0.113***	-0.190***
	(0.019)	(0.023)	(0.024)	(0.024)	(0.023)	(0.027)	(0.031)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Female-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,190,870	2,863,950	2,863,800	2,863,950	2,863,800	1,140,200	1,640,320
Inventor-level regressions							
Post	-0.129***	-0.982***	-0.229***	-1.427***	-0.649***	-0.097***	-0.102**
	(0.016)	(0.034)	(0.017)	(0.029)	(0.014)	(0.014)	(0.042)
Post × Female	-0.086***	-0.098***	-0.082***	-0.129***	-0.175***	-0.049**	-0.061**
	(0.013)	(0.025)	(0.020)	(0.020)	(0.016)	(0.019)	(0.030)
Constant	1.796***	4.808***	2.703***	2.947***	0.835***	0.776***	4.564***
	(0.008)	(0.009)	(0.007)	(0.006)	(0.005)	(0.007)	(0.020)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	617,152	553,562	553,546	553,562	553,546	225,892	321,808
OLS regressions							
	Log(Total patents)	Log(Citations)	Log(Scaled citations)	Log(Citations per patent)	Log(Scaled citations per patent)	Log(Top 10% cited patents)	Log(Market value)
SC	-0.123***	-0.243***	-0.087***	-0.228***	-0.078***	-0.015***	-0.023***
	(0.007)	(0.012)	(0.005)	(0.010)	(0.003)	(0.001)	(0.006)
SC × Female	-0.013***	0.043***	0.004	0.040***	0.005**	-0.001	-0.046***
	(0.003)	(0.007)	(0.003)	(0.006)	(0.002)	(0.001)	(0.009)
Observations	3,192,690	3,192,690	3,192,690	3,192,690	3,192,690	3,192,690	3,188,970
R-squared	0.398	0.362	0.382	0.302	0.297	0.326	0.051
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Alternative measures of patenting productivity

	Frac solo-inventor patent	Weighted patent	Number of fields	Top 5% cited patents	Market value per patent	Likelihood of inventor attrition in year [t,t+3]	Likelihood of inventor attrition in year [t,t+4]	Likelihood of inventor attrition in year [t,t+5]
SC	-0.544***	-0.321***	-0.378***	-0.212***	-0.361***	1.653***	1.471***	1.233***
	(0.024)	(0.020)	(0.018)	(0.021)	(0.040)	(0.0701)	(0.0728)	(0.0696)
SC × Female	-0.175***	-0.086***	-0.114***	-0.102***	-0.084***	0.182***	0.204***	0.313***
	(0.034)	(0.016)	(0.011)	(0.027)	(0.024)	(0.0332)	(0.0344)	(0.0357)
Constant	-1.762***	-0.942***	-0.342***	-1.482***	1.822***			
	(0.021)	(0.015)	(0.018)	(0.021)	(0.044)			
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	965,290	3,190,870	3,187,700	702,510	1,640,320	2,411,500	2,194,590	2,032,470

Panel C: Local immigration enforcement policies

	Quantity	Quality					Value
	Total patents	Citations	Scaled citations	Citations per patent	Scaled citations per patent	Top 10% cited patents	Market value
SC	-0.284***	-0.282***	-0.227***	-0.428***	-0.358***	-0.204***	-0.234***
	(0.025)	(0.026)	(0.025)	(0.026)	(0.025)	(0.025)	(0.051)
SC × Female	-0.088***	-0.051***	-0.085***	-0.069***	-0.114***	-0.066***	-0.068***
	(0.012)	(0.018)	(0.017)	(0.018)	(0.016)	(0.019)	(0.026)
g287	-0.192***	-0.191***	-0.192***	-0.221***	-0.218***	-0.208***	-0.278***
	(0.060)	(0.060)	(0.064)	(0.065)	(0.073)	(0.070)	(0.092)
g287 × Female	-0.041	-0.076	-0.090*	-0.073	-0.101*	-0.090*	-0.021
	(0.045)	(0.058)	(0.054)	(0.062)	(0.059)	(0.051)	(0.099)
Constant	-0.072***	3.103***	0.743***	2.074***	-0.315***	-1.088***	2.679***
	(0.013)	(0.013)	(0.014)	(0.013)	(0.015)	(0.015)	(0.032)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,190,870	2,863,950	2,863,800	2,863,950	2,863,800	1,140,200	1,640,320

Panel D: Subsamples

	Quantity						Value
	Total patents	Citations	Scaled citations	Citations per patent	Scaled citations per patent	Top 10% cited patents	Market value
Excluding early adopters of SC program							
SC	-0.325***	-0.320***	-0.466***	-0.267***	-0.400***	-0.243***	-0.296***
	(0.018)	(0.023)	(0.022)	(0.018)	(0.017)	(0.018)	(0.036)
SC × Female	-0.085***	-0.052***	-0.070***	-0.086***	-0.113***	-0.062***	-0.065**
	(0.013)	(0.018)	(0.018)	(0.018)	(0.017)	(0.020)	(0.026)
Constant	-0.103***	3.086***	0.723***	2.045***	-0.347***	-1.111***	2.631***
	(0.013)	(0.013)	(0.013)	(0.012)	(0.013)	(0.013)	(0.031)
Inventor &Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,041,920	2,730,430	2,730,430	2,730,280	2,730,280	1,092,430	1,559,090
Excluding Asian inventors							
SC	-0.307***	-0.311***	-0.459***	-0.250***	-0.385***	-0.223***	-0.256***
	(0.020)	(0.021)	(0.020)	(0.020)	(0.018)	(0.020)	(0.043)
SC × Female	-0.139***	-0.107***	-0.114***	-0.145***	-0.167***	-0.115***	-0.117***
	(0.016)	(0.023)	(0.022)	(0.024)	(0.021)	(0.027)	(0.026)
Constant	-0.109***	3.096***	0.728***	2.074***	-0.321***	-1.094***	2.672***
	(0.015)	(0.013)	(0.014)	(0.014)	(0.016)	(0.015)	(0.034)
Inventor & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,859,340	2,563,170	2,563,170	2,563,020	2,563,020	1,006,480	1,424,090
Excluding Hispanic inventors							
SC	-0.302***	-0.306***	-0.454***	-0.246***	-0.379***	-0.222***	-0.261***
	(0.020)	(0.022)	(0.021)	(0.020)	(0.018)	(0.020)	(0.041)
SC × Female	-0.085***	-0.051***	-0.068***	-0.085***	-0.111***	-0.063***	-0.059**
	(0.013)	(0.018)	(0.018)	(0.017)	(0.016)	(0.019)	(0.026)
Constant	-0.074***	3.099***	2.067***	0.740***	-0.320***	-1.092***	2.674***
	(0.014)	(0.014)	(0.014)	(0.015)	(0.017)	(0.016)	(0.035)
Inventor & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,075,220	2,762,270	2,762,270	2,762,120	2,762,120	1,102,850	1,581,420
Excluding boarder counties							
SC	-0.306***	-0.315***	-0.251***	-0.461***	-0.382***	-0.229***	-0.262***
	(0.021)	(0.022)	(0.020)	(0.022)	(0.019)	(0.020)	(0.043)
SC × Female	-0.090***	-0.050**	-0.087***	-0.068***	-0.114***	-0.064***	-0.074***
	(0.013)	(0.019)	(0.018)	(0.019)	(0.017)	(0.021)	(0.026)
Constant	-0.094***	3.081***	0.723***	2.050***	-0.335***	-1.106***	2.662***
	(0.015)	(0.015)	(0.016)	(0.015)	(0.017)	(0.017)	(0.036)
Inventor & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,085,950	2,768,130	2,767,980	2,768,130	2,767,980	1,100,060	1,579,870

Internet Appendix: Additional Tables

Table IA.1. Falsification test: Undocumented labor supply in agriculture & construction

This table presents evidence on the falsification test using undocumented labor supply in agriculture & construction. Column (1) reports the first analysis, which validates SC's negative effect on the supply of undocumented immigration labor in agriculture and construction. We regress the employment of likely undocumented immigrants in these industries in a county-year on the rollout status of SC in that county for that year, controlling for county and year fixed effects. In the second analysis, we assess whether the supply of undocumented immigrant labor in agriculture & construction might be the mechanism through which SC widened gender gap in invention. We obtain from the first analysis the predicted values of employment of likely undocumented immigrants in these industries—variable *Predicted undocumented immigrants* for each county-year—and map it to the inventor-level sample according to each inventor's residential address each year. We then perform Poisson regression and report the results in columns (2)-(8). Outcome variable takes the value of one of the innovation outcome measures for an inventor in a given year. *Female* is a dummy variable that takes the value of one if the inventor is female and zero otherwise. Standard errors clustered at the inventor level are reported in parentheses below each point estimate. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Definitions of all variables are provided in Appendix A.

	Annual hours worked in agriculture & construction	Quantity	Quality					Value
	Likely undocumented immigrants	Total patents	Citations	Scaled citations	Citations per patent	Scaled citations per patent	Top 10% cited patents	Market value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SC	-0.529*							
	(0.320)							
Female×Predicted undocumented immigrants		0.013	-0.023	0.010	-0.025	0.011	0.011	0.009
		(0.011)	(0.017)	(0.014)	(0.018)	(0.015)	(0.017)	(0.020)
Predicted undocumented immigrants		0.581***	0.555***	0.451***	0.850***	0.728***	0.418***	0.521***
		(0.058)	(0.055)	(0.053)	(0.058)	(0.054)	(0.052)	(0.106)
	9.408***	-5.510***	-2.047***	-3.459***	-5.854***	-7.137***	-4.978***	-2.183**
	(0.216)	(0.547)	(0.502)	(0.498)	(0.536)	(0.508)	(0.489)	(1.035)
Inventor FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.936							
Observations	2,934	1,975,708	1,776,461	1,776,402	1,776,461	1,776,402	715,306	1,066,916

Table IA.2. Rollout of Secure Communities and the gender gap in patenting productivity: the role of parenthood by age group

This table reports Poisson regression estimates of the relation between the rollout of the SC program and the patenting productivity across male and female inventors, interacted with the age group of the inventor. Standard errors clustered at the inventor level are reported in parentheses below each point estimate. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

	Quantity	Quality					Value
	Total patents	Citations	Scaled citations	Citations per patent	Scaled citations per patent	Top 10% cited patents	Market value
SC × Female × Age[31-45]	-0.109***	-0.137***	-0.128**	-0.093**	-0.099**	-0.126**	-0.064
	(0.025)	(0.053)	(0.054)	(0.041)	(0.040)	(0.052)	(0.042)
SC × Female × Age[46-65]	-0.096***	-0.098*	-0.112**	-0.068	-0.091**	-0.083	-0.005
	(0.032)	(0.057)	(0.052)	(0.046)	(0.043)	(0.061)	(0.058)
SC × Female × Age[66-79]	-0.233**	-0.163	-0.061	-0.179	-0.048	0.075	-0.257
	(0.095)	(0.151)	(0.196)	(0.148)	(0.162)	(0.212)	(0.215)
Female × Age[31-45]	0.017	0.058	0.037	0.049	0.032	0.035	0.034
	(0.023)	(0.044)	(0.043)	(0.035)	(0.032)	(0.043)	(0.035)
Female × Age[46-65]	-0.002	0.042	-0.012	0.041	0.018	-0.027	-0.042
	(0.032)	(0.057)	(0.057)	(0.046)	(0.047)	(0.062)	(0.057)
Female × Age[66-79]	0.064	-0.054	-0.178	0.065	-0.051	-0.317	-0.091
	(0.101)	(0.151)	(0.162)	(0.135)	(0.140)	(0.208)	(0.225)
SC × Age[31-45]	-0.220***	-0.248***	-0.254***	-0.216***	-0.213***	-0.242***	-0.235***
	(0.014)	(0.020)	(0.018)	(0.017)	(0.015)	(0.019)	(0.024)
SC × Age[46-65]	-0.387***	-0.440***	-0.440***	-0.371***	-0.365***	-0.421***	-0.467***
	(0.018)	(0.023)	(0.021)	(0.023)	(0.021)	(0.022)	(0.032)
SC × Age[66-79]	-0.623***	-0.612***	-0.621***	-0.498***	-0.513***	-0.632***	-0.656***
	(0.025)	(0.044)	(0.040)	(0.041)	(0.035)	(0.042)	(0.055)
Age[31-45]	0.230***	0.183***	0.238***	0.125***	0.169***	0.223***	0.256***
	(0.013)	(0.014)	(0.014)	(0.011)	(0.012)	(0.015)	(0.024)
Age[46-65]	0.287***	0.207***	0.297***	0.137***	0.217***	0.275***	0.341***
	(0.013)	(0.021)	(0.019)	(0.020)	(0.019)	(0.023)	(0.024)
Age[66-79]	0.222***	0.112***	0.217***	0.042	0.142***	0.206***	0.067
	(0.022)	(0.037)	(0.037)	(0.034)	(0.032)	(0.042)	(0.049)
SC × Female	-0.034	0.002	-0.034	-0.044	-0.085**	-0.019	-0.049
	(0.026)	(0.047)	(0.045)	(0.038)	(0.035)	(0.047)	(0.050)
SC	-0.107***	-0.093***	-0.030	-0.275***	-0.202***	-0.018	-0.061
	(0.024)	(0.026)	(0.025)	(0.022)	(0.023)	(0.025)	(0.046)
Constant	-0.379***	2.825***	0.425***	1.888***	-0.528***	-1.341***	2.397***
	(0.017)	(0.019)	(0.018)	(0.017)	(0.018)	(0.017)	(0.038)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,645,220	2,366,640	2,366,510	2,366,640	2,366,510	882,300	1,332,110