

# The role of stigma in matching, relationship stability, asset ownership and earnings of same-sex couples in the US \*

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## Abstract

This paper extends the dynamic overlapping generations model to incorporate societal stigma as a determining factor in influencing marriage stability, savings, asset ownership, and earning opportunities for same-sex couples. Using the SIPP panel for detailed data on marriage dynamics and asset ownership, and the PRRI-AVS survey data to construct a state-level index of societal stigma on same sex marriage, I employ Probit and High-Dimensional Fixed Effects (HDFE) regressions to find that stigma imposes a significant negative effect on household earnings, confirming a structural wage penalty. Crucially, stigma drives a distortion in portfolio composition: it creates a substantial penalty on high-yield Financial Asset ownership (stocks, bonds) while showing a positive association with the holding of liquid Savings Instruments (cash accounts). This evidence supports a Precautionary Liquidity Preference mechanism, where couples rationally substitute away from illiquid assets to hedge against heightened relationship and economic instability. This behavioral response, compounded by low real estate ownership likely due to supply-side discrimination, suggests that stigma creates a persistent long-run wealth gap by forcing inefficient portfolio allocation, with the effect being most acute for non-White female couples (Triple Jeopardy).

**Keywords:** stigma, marriage, divorce, assets, same-sex couples

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## 1 INTRODUCTION

The legalization of same-sex marriage in the US in 2014 was a landmark moment that promised marital equality to same-sex couples. However, evidence on the economic gains for same-sex couples from the favorable legal landscape remains ambiguous. Despite gains in employment probabilities among individuals in same-sex couples ([Sansone \(2019\)](#)), reduction in hate crimes ([Nikolaou \(2022\)](#)) and reduction in STIs ([Carpenter et al. \(2021\)](#)), significant increases in marital surplus and home-ownership returns tied to relationship duration ([Delhommer and Hamermesh \(2021\)](#)), many studies are more sceptic about the economic benefits of legalization. Using national mortgage data, [Sun and Gao \(2019\)](#) found that same-sex couples were 73% more likely to be denied a mortgage than different-sex couples with similar financial profiles and were charged higher interest rates and fees despite having no higher default risk. [Hagendorff et al. \(2022\)](#) reaches a similar conclusion and finds that the mortgage loan denial gap between same-sex and different-sex applicants increased after marriage legalization. [Jepsen and Jepsen \(2009\)](#) uses census data to establish that same-sex couples have lower homeownership rates than different-sex couples; although they often have higher homeownership rates than unmarried different-sex cohabiting couples, suggesting that marriage is a driver in real-estate accumulation. In an earlier study, [Leppel \(2007\)](#) uses a decomposition analysis to find that although income accounts for part of the homeownership gap, a significant portion remains unexplained by economic variables. Even when renting homes, [Hellyer \(2021\)](#) finds that same-sex couples face significant barriers while renting.

In a recent study, [Carpenter et al. \(2025\)](#) finds that LGB individuals are less likely to have “rainy day” savings funds as compared to similarly situated heterosexuals, even after controlling for education and income suggesting social vulnerabilities. Previous studies by [Schneebaum and Badgett \(2019\)](#) have found that lesbian couples are likely to have higher poverty rates than gay male or heterosexual married couples due to the gender wage gap affecting both earners, despite high labor force participation. These studies suggest that for gender and sexual minorities, stigma cause victimiza-

tion (Hatzenbuehler et al. (2024), Bränström et al. (2023)), and affect their ability to maintain a stable household structure and accumulate wealth (Badgett et al. (2024)).

This paper develops a dynamic overlapping-generations (OLG) search-and-matching model in which stigma directly affects both the surplus of LGBTQ+ marriages and the divorce hazard. The framework connects stigma to marital stability, savings and household asset ownership. The model produces novel comparative statics: higher stigma reduces marriage rates, increases divorce probabilities, lowers household wealth, and amplifies wealth inequality between LGBTQ+ and different-sex couples. The empirical strategy leverages the Survey of Income and Program Participation (SIPP hereafter) panel of the Census Bureau for the period between 2014 and 2024, following the legalization of same-sex marriages in the US. The panel has detailed information on marital dynamics, earnings and asset ownership. To measure stigma, I use state-level data from Public Religion Research Institute's (PRRI) American Value Survey (AVS henceforth). The AVS records the attitudes of individuals on same sex marriage for a representative sample as a repeated cross-section and releases the data at the state level. The study aims to understand the economic consequences of stigma for same-sex couples compared to their different-sex counterparts. A goal of this project is also to examine marriage heterogeneity by gender composition (male vs female couples) and contribute to the design of policies aimed at reducing economic disparities and promoting financial stability among marginalized communities.

This project thus, has multifaceted relevance. On a societal level, understanding these dynamics is crucial to designing policies that helps realize the benefits of marriage equality and social inclusion. From an economic perspective, the study has broader implications on labor supply decisions, savings decisions, asset ownership and inequality. In a broader sense, this analysis contributes to the growing literature on the intersection of social identity, economic behavior, economic outcomes, and public policy.

Studies on social attitudes have consistently shown that societal acceptance of LGBTQ+ individuals varies significantly across states and regions, and has significant correlation with differences in marriage rates, divorce rates and economic outcomes ([Badgett \(2003\)](#), [Carpenter and Eppink \(2017\)](#)). This project uses the American Values Survey (AVS) which explicitly records societal attitudes towards same-sex marriage through a representative national survey, to gain a more focused understanding of how these attitudes shape marital stability and economic prospects of same-sex households.

This paper is structured as follows. Section 2 presents a brief legal and social history of same-sex marriages in the US. In section 3, I develop a dynamic OLG model of marriage market dynamics, incorporating stigma and derive conditions to analyze its impact on dissolution of marriage and equilibrium savings. Section 4 proceeds to a discussion of the empirical strategy used to examine the model, including a description of the data sources and estimation techniques used. I discuss the main results from the analysis in Section 5, and check for robustness of the results. Section 6 concludes with a discussion of the main takeaways of the paper and potential policy implications of the results.

## 2 SAME-SEX MARRIAGES IN THE US

The history of same-sex marriage in the United States is a long and complex evolution marked by shifting societal attitudes, legal battles, and significant milestones. While marriage between individuals of the same gender was largely unrecognized for most of American history, the late 20th and early 21st centuries saw transformative changes that led to nationwide legalization. The economic implications of same-sex marriage have also played a crucial role in shaping policy and public opinion.

Historically, American laws and social norms were deeply rooted in religious and cultural beliefs that defined marriage as a union between a man and a woman. Throughout the 19th and early 20th centuries, any deviation from different-sex relationships was often met with criminalization and social stigma. Sodomy laws, which

targeted same-sex relations, were enforced in many states, reinforcing the marginalization of LGBTQ+ individuals.

Economically, same-sex couples faced significant barriers, particularly regarding joint property ownership, inheritance laws, and financial benefits tied to marriage. The inability to legally marry meant exclusion from tax benefits, healthcare access, and spousal retirement benefits, which placed many LGBTQ+ individuals at a financial disadvantage.

Despite legal and social barriers, LGBTQ+ communities began to emerge and organize in the mid-20th century. The 1969 Stonewall Riots in New York City marked a pivotal moment in the fight for LGBTQ+ rights, igniting a movement that sought equality in various facets of life, including financial security through marriage rights.

The first significant legal challenge for same-sex marriage emerged in 1971 when Jack Baker and Michael McConnell applied for a marriage license in Minnesota. Their case, *Baker v. Nelson*, reached the U.S. Supreme Court, which dismissed it, indicating that same-sex marriage had no legal standing at the time.

Throughout the 1980s and 1990s, advocacy groups continued to push for marriage rights, although progress was slow. In response, many states enacted laws explicitly banning same-sex marriage. In 1996, Congress passed the Defense of Marriage Act (DOMA), which defined marriage at the federal level as a union between one man and one woman, preventing federal recognition of same-sex marriages even if states chose to legalize them.

This legal exclusion had significant economic consequences. Same-sex couples were denied Social Security survivor benefits, tax advantages, and employer-provided health insurance that different-sex married couples enjoyed. Financial inequalities further highlighted the necessity of legal recognition for same-sex unions.

The first major legal victory came in 2003 when the Massachusetts Supreme Judicial Court ruled in *Goodridge v. Department of Public Health* that denying same-sex couples the right to marry was unconstitutional. This decision made Massachusetts the first state to legalize same-sex marriage, paving the way for other states to follow suit. Over the next decade, several states legalized same-sex marriage through court rulings, legislative action, or voter referendums, while others maintained bans.

A crucial turning point came in 2013 when the U.S. Supreme Court struck down a key provision of DOMA in *United States v. Windsor*. This ruling ensured that the federal government recognized same-sex marriages performed in states where it was legal, granting couples equal access to federal benefits. Economically, this provided same-sex couples with tax relief, inheritance rights, and financial stability that had long been denied to them.

The momentum culminated in 2015 with the landmark Supreme Court case *Obergefell v. Hodges*. The Court ruled in a 5-4 decision that same-sex marriage bans were unconstitutional under the Fourteenth Amendment, effectively legalizing same-sex marriage throughout the United States. This ruling granted same-sex couples the same legal rights, protections, and financial benefits as different-sex couples.

The economic impact of legalizing same-sex marriage was substantial. Studies estimated that marriage equality contributed billions of dollars to the U.S. economy through increased wedding-related spending, reduced social welfare dependency, and expanded tax revenues ([Gates \(2014b\)](#), [Badgett \(2009b\)](#)). Businesses catering for weddings, from venues to florists and travel agencies, experienced a surge in revenue ([Badgett \(2009a\)](#)). Furthermore, same-sex spouses gained access to employer-sponsored benefits, reducing financial burdens and increasing economic security for LGBTQ+ families ([Gates \(2014a\)](#)).

Following this decision, the social acceptance of same-sex marriage increased, with polls showing increasing support among Americans. However, legal and social challenges persisted, particularly concerning religious objections and anti-discrimination

protections for LGBTQ+ individuals. Some states and private organizations sought ways to limit the application of *Obergefell*, leading to further legal battles over issues such as adoption rights, religious exemptions, and health care protections.

### 3 THE MODEL

In this section, I develop a dynamic Overlapping Generations (OLG) framework to present a unified model of how societal stigma may impact matching decisions, reduce the marital surplus for same-sex couples, increase the chances of marriage dissolution and affect savings decisions and ownership of assets for same-sex couples. The choice of OLG framework for this analysis, over other household or dynamic general equilibrium models, is because the OLG model allows us to analyze the impact of stigma over time and also gives meaningful predictions about how stigma may impact multiple variables, as mentioned. In that sense, the OLG framework allows us to create a unified model of matching, marital stability and asset ownership.

The framework distinguishes heterosexual and homosexual individuals, who are otherwise identical (same productivity, preferences, etc.). Each agent lives for multiple periods in an overlapping generations framework: in youth, singles search for partners; in marriage, couples jointly consume and save; marriages may dissolve, ending joint savings and asset ownership opportunities. I assume separate marriage markets for different-sex and same-sex couples. Consistent with Becker (1974), a married couple produces household goods (meals, leisure, companionship, etc.) via pooled time and income. I assume full pooling: spouses share consumption and joint output.

#### 3.1 Environment, timing, and types

Time is discrete,  $t = 0, 1, 2, \dots$ . Each cohort lives two adult periods: *young* at  $t$ , then *old* at  $t + 1$ . Let the population of young be normalized to one in every period. Individuals belong to type  $g \in \{H, G\}$ :  $H$  (heterosexual) and  $G$  (LGB). Except for stigma, all primitives (preferences, incomes, technology) are the same across  $g$ . Each

young agent is either single or matched.

Sequence within a cohort's life (two-period timing):

1. *Start of youth (period  $t$ ):* the agent chooses search intensity  $e \geq 0$  and pays cost  $k(e)$  (twice continuously differentiable,  $k'(e) > 0$ ,  $k''(e) > 0$ ).
2. A Poisson meeting occurs within the period with arrival rate  $\alpha_g(e)$  (increasing, concave; benchmark  $\alpha_g(e) = \lambda_g e^{\frac{1}{2}}$ ,  $\lambda_g > 0$ ). If a meeting occurs, the pair draws an *idiosyncratic match quality*  $\varepsilon \sim F_g$  (continuous CDF). They accept marriage if the expected value of marrying exceeds the value of remaining single (reservation rule below).
3. At the *end of youth*, after the marriage acceptance decision, the agent chooses *savings*  $s \geq 0$  and youth consumption  $c_1$ .
4. *At the start of old age (period  $t + 1$ ):* a married agent faces a divorce shock with probability  $\delta_g \in (0, 1)$ . If divorce occurs, joint assets are split; otherwise the couple remains married. Old consumption  $c_2$  is then realized; the life ends.

I assume a small open economy with exogenous gross return  $1 + r > 1$  (this keeps focus on marriage dynamics and asset ownership without adding production notation). Extensions to general equilibrium with  $(1 + r)$  and wages  $w$  determined by a production function are straightforward.

### 3.2 Preferences, resources, stigma, and divorce

Per-period felicity is  $u(c)$ , strictly increasing and concave (benchmark  $u(c) = \log c$ ). Lifetime utility is

$$U = u(c_1) + \beta \mathbb{E}[u(c_2) + \mathbf{1}\{\text{married in old}\} \cdot (M - \tau_g)],$$

where:

-  $M > 0$  is the *per-person marital surplus* from joint household public goods (companionship, economies of scale, etc.).

- $\tau_g$  is the **stigma penalty** per married period:  $\tau_H = 0$  for heterosexual couples;  $\tau_G \equiv \tau \geq 0$  for LGB couples. Thus the net marital flow term is  $M - \tau_g$ . A larger  $\tau$  mechanically reduces the net payoff from same-sex marriage.
- $\beta \in (0, 1)$  is the time discount factor.

Endowments/incomes (per person):

- *Young* endowment (labor net of taxes etc.):  $y_1 \sim G_1(y)$ .

*Old* endowment if single:  $y_2 \sim G_2(y)$ .

Here  $G_1$  and  $G_2$  are continuous distributions with finite support.

- I assume the *budget set* does not change with marital status except for asset division in divorce (see below). Hence, the marriage flow benefit  $M - \tau_g$  is modeled as utility (a standard and transparent way to embed stigma).

Let  $a$  denote assets at the end of youth (essentially,  $a = s$ ). The youth budget is

$$c_1 + s + k(e) = y_1.$$

At the start of old age, assets grow to  $(1+r)s$ . If the individual is *single* in old age, consumption is

$$c_2^S = (1+r)s + y_2.$$

If *married* in old age and *no divorce* occurs (probability  $1 - \delta_g$ ), I take consumption resources *per person* to be the same  $(1+r)s + y_2$  (I keep resource differences in the utility flow  $M - \tau_g$  to isolate stigma cleanly). If *divorce* occurs (probability  $\delta_g$ ), I assume that the joint assets,  $2(1+r)s$ , are split with a share  $\eta \in (0, 1)$  for each spouse, while individual incomes  $y_2$  remain private. Symmetry  $\eta = 0.5$  is the benchmark; deviations capture bargaining power or institutional/legal asymmetries. There is a per-person resource loss  $\xi \geq 0$  (legal/relocation costs). Hence,

$$c_2^M = (1+r)s + y_2 \quad (\text{remain married}), \quad c_2^D + \xi = \eta(2(1+r)s) + y_2, \quad \eta \in (0, 1) \quad (\text{divorce}).$$

### 3.3 Search, matching, and acceptance

Given search intensity  $e$ , meetings arrive via a Poisson process with rate  $\alpha_g(e)$ . For small interval  $\Delta t$ ,

$$\Pr(\text{meeting in } \Delta t) \approx \alpha_g(e)\Delta t.$$

Conditional on a meeting, match quality  $\varepsilon \sim F_g$  augments the marital flow benefit additively, so the old-age marital utility flow becomes  $(M + \varepsilon - \tau_g)$  if still married. The *acceptance rule* compares the expected old-age payoff from marrying now vs staying single. Because marriage only affects old-age flow utility (and divorce risk), the acceptance is a *reservation rule in  $\varepsilon$* :

$$\text{Accept} \iff \Delta V_g(s, \varepsilon) \geq 0,$$

where the expected gain (relative to staying single) if one marries at the end of youth with assets  $s$  is

$$\begin{aligned} \Delta V_g(s, \varepsilon) = & \underbrace{(1 - \delta_g)[u((1+r)s + y_2) + (M + \varepsilon - \tau_g)]}_{\text{stay married}} + \underbrace{\delta_g u(\eta(1+r)s + y_2 - \xi)}_{\text{divorce}} \\ & - \underbrace{u((1+r)s + y_2)}_{\text{remain single}} \end{aligned}$$

This simplifies to

$$\Delta V_g(s, \varepsilon) = (1 - \delta_g)(M + \varepsilon - \tau_g) + \delta_g [u(\eta(1+r)s + y_2 - \xi) - u((1+r)s + y_2)].$$

Define the *reservation match quality*  $\varepsilon_g^*(s)$  by  $\Delta V_g(s, \varepsilon_g^*(s)) = 0$ . Then

$$\varepsilon_g^*(s) = \tau_g - M - \frac{\delta_g}{1 - \delta_g} [u(\eta(1+r)s + y_2 - \xi) - u((1+r)s + y_2)].$$

Hence the *acceptance probability* conditional on meeting is

$$p_g(s) = 1 - F_g(\varepsilon_g^*(s)).$$

Furthermore, conditional on meeting, marriage occurs with probability  $p_g(s) = 1 - F_g(\varepsilon_g^*(s))$ . Thus, the hazard of exiting the unmarried state within youth, or the *marriage hazard* within youth is

$$\mu_g(e, s) = \alpha_g(e) p_g(s).$$

which is the product of the arrival intensity and acceptance probability: the conditional probability of marriage given still unmarried.

The key insights from the threshold are:

1. Higher stigma  $\tau_g$  raises  $\varepsilon_g^*(s)$ , decreases  $p_g(s)$  and thus decreases  $\mu_g(e, s)$ .
2. Higher divorce hazard  $\delta_g$  also raises the threshold (the second term is negative because  $u(\eta(1+r)s + y_2 - \xi) < u((1+r)s + y_2)$  for  $\eta < 1$  or  $\xi > 0$ ), thus lowering  $p_g(s)$ .

### 3.4 The young agent's problem

The young chooses  $(e, s, c_1)$  to maximize expected lifetime utility. Because the marriage decision is made before saving/consumption choices are finalized at the end of youth, I can write the *expected old-age utility* conditional on  $(e, s)$  as

$$\begin{aligned} \mathcal{U}_2^g(e, s) = & \left(1 - \mu_g(e, s)\right) u((1+r)s + y_2) + \mu_g(e, s) \left[ (1 - \delta_g) \left( u((1+r)s + y_2) \right. \right. \\ & \left. \left. + \mathbb{E}[M + \varepsilon - \tau_g \mid \varepsilon \geq \varepsilon_g^*(s)] \right) + \delta_g u(\eta(1+r)s + y_2 - \xi) \right]. \end{aligned}$$

Let  $\bar{\varepsilon}_g(s) \equiv \mathbb{E}[\varepsilon \mid \varepsilon \geq \varepsilon_g^*(s)]$  be the *truncated mean* of match quality. Then

$$\begin{aligned} \mathcal{U}_2^g(e, s) = & u((1+r)s + y_2) + \mu_g(e, s) \left\{ (1 - \delta_g) \left[ M - \tau_g + \bar{\varepsilon}_g(s) \right] + \delta_g \left[ u(\eta(1+r)s + y_2 - \xi) \right. \right. \\ & \left. \left. - u((1+r)s + y_2) \right] \right\} \end{aligned}$$

The young's objective is

$$\max_{e \geq 0, s \geq 0, c_1 \geq 0} u(c_1) + \beta \mathcal{U}_2^g(e, s) \quad \text{s.t.} \quad c_1 + s = y_1 - k(e).$$

Eliminate  $c_1$  via the budget to write the problem in  $(e, s)$ . Let  $c_1(e, s) \equiv y_1 - k(e) - s$ ,  $c_2^S(s) \equiv (1+r)s + y_2$ ,  $c_2^D(s) \equiv \eta(1+r)s + y_2 - \xi$ . Using  $\mu_g(e, s) = \alpha_g(e)p_g(s)$ , the Lagrangian-free first-order conditions yielding the Euler's equations are:

$$\begin{aligned}
& - \underbrace{u'(c_1(e, s))}_{\substack{\text{marginal utility} \\ \text{cost when young}}} + \beta \left[ \underbrace{(1 - \mu_g)(1 + r) u'(c_2^S(s))}_{\substack{\text{return if single in old age}}}
\right. \\
& \quad + \underbrace{\mu_g(1 - \delta_g)(1 + r) u'(c_2^S(s))}_{\substack{\text{married and remain married}}} \\
& \quad + \underbrace{\mu_g \delta_g \eta(1 + r) u'(c_2^D(s))}_{\substack{\text{married then divorce}}} \\
& \quad + \underbrace{\alpha_g(e) p'_g(s) \Gamma_g(s)}_{\substack{\text{threshold effect via } p'_g(s); \\ \text{acceptance-probability (threshold) effect}}} \quad + \underbrace{\mu_g(1 - \delta_g) \frac{d\bar{\varepsilon}_g}{ds}}_{\substack{\text{truncated-mean (composition) effect}}} \Big] = 0,
\end{aligned}$$

where the left-hand side indicates the trade-off between utility when young and utility when old.  $\Gamma_g(s)$  is the *marriage surplus in utility units*:

$$\Gamma_g(s) \equiv (1 - \delta_g) [M - \tau_g + \bar{\varepsilon}_g(s)] + \delta_g [u(c_2^D(s)) - u(c_2^S(s))].$$

and

$$\frac{d\bar{\varepsilon}_g}{ds} = \frac{f_g(\varepsilon_g^*(s))}{1 - F_g(\varepsilon_g^*(s))} (\bar{\varepsilon}_g(s) - \varepsilon_g^*(s)) \frac{d\varepsilon_g^*}{ds},$$

with

$$\frac{d\varepsilon_g^*}{ds} = -\frac{\delta_g}{1 - \delta_g} \left[ u'(\eta(1+r)s + y_2 - \xi) \eta(1+r) - u'((1+r)s + y_2) (1+r) \right],$$

and

$$p'_g(s) = -f_g(\varepsilon_g^*(s)) \frac{d\varepsilon_g^*}{ds}.$$

The acceptance probability threshold effect captures how a marginal change in savings shifts the reservation cutoff and hence the acceptance probability (the “threshold” channel). The truncated mean (composition) effect captures how the truncated mean of matched quality, conditional on acceptance, changes as the cutoff moves (the “composition” channel). The Euler equation is discussed further with some special cases in Appendix B.

The term  $p'_g(s)$  (via  $\varepsilon_g^*(s)$ ) captures that savings change the acceptance threshold and thus the chance of being married; with log utility and common functional forms this term can be signed (see remarks below).

A common and transparent simplification—used widely in the search literature (for instance, in Mortensen and Pissarides (1999); Rogerson et al. (2005))—is to treat idiosyncratic match quality as realized after the savings decision within period, so  $p_g$  does not depend on  $s$  at the margin (i.e.,  $p'_g(s) = 0$ ). This prevents individuals from manipulating savings to influence meeting outcomes within the same period. It simplifies dynamics without distorting long-run comparative statics. Under that (standard) timing,

$$u'(c_1) = \beta(1+r) \left[ (1-\mu_g)u'(c_2^S) + \mu_g \left( (1-\delta_g)u'(c_2^S) + \delta_g \eta u'(c_2^D) \right) \right].$$

This is the **Euler condition**: the marginal utility cost of saving today equals the discounted expected marginal utility benefit tomorrow, averaging over being single, married/no-divorce, and married/divorce.

The key insight from this result is that, a *higher divorce risk*  $\delta_g$  and/or more severe division cost (smaller  $\eta$ , larger  $\xi$ ) reduces the expected return to saving (because more mass shifts to  $u'(c_2^D)$  and  $\eta < 1$ ), lowering the optimal  $s$ . Stigma  $\tau_g$  affects saving only indirectly through its effect on  $\mu_g$  (fewer marriages → lowers the weight on the married states).

The Lagrangian derivative is

$$\frac{\partial \mathcal{U}}{\partial e} = -k'(e) + \beta \alpha'_g(e) p_g(s) \Gamma_g(s).$$

At optimum  $e^*$ :

$$k'(e^*) = \beta \alpha'_g(e^*) p_g(s^*) \Gamma_g(s^*).$$

The marginal cost of search ( $k'(e)$ ) equals the discounted expected utility gain from higher meeting intensity: more meetings  $\alpha'_g(e)$ , scaled by acceptance probability  $p_g$ , and expected surplus  $\Gamma_g$ . This indicates that  $\Gamma_g$  is decreasing in stigma  $\tau_g$  and decreasing in divorce risk  $\delta_g$ . Thus, ceteris paribus,  $\tau$  and  $\delta$  depress the optimal search intensity  $e^*$ , reducing the marriage hazard  $\mu_g$ .

### 3.5 Steady-state marriage rates and assets

#### 3.5.1 Marriage stock dynamics and steady state

Let  $m_t^g$  denote the share of older individuals of type- $g$ , married at time  $t$ . Each cohort is replaced by the next, following the structure of overlapping generations. The law of motion induced by the within-cohort marriage flow:

$$m_{t+1}^g = (1 - \delta_g) m_t^g + \mu_g(e_t^*, s_t^*) (1 - m_t^g).$$

follows because old-age marriages persist unless divorced, while new youth enter with marriage probability  $\mu_g$ . The stationary steady state  $m^{g*}$  represents the long-run stable fraction of married individuals in the population. In a stationary steady state,  $m_{t+1}^g = m_t^g \equiv m^{g*}$ , hence

$$m^{g*} = \frac{\mu_g(e^*, s^*)}{\mu_g(e^*, s^*) + \delta_g}.$$

Comparative statics:  $\partial m^{g*}/\partial \mu_g > 0$ ,  $\partial m^{g*}/\partial \delta_g < 0$ . Since  $\mu_g = \alpha_g(e^*) p_g(s^*)$  falls with  $\tau_g$  via  $p_g$  and  $e^*$ , it follows that higher stigma lowers the steady-state marriage

share. Higher divorce hazard directly lowers  $m^{g*}$ .

### 3.5.2 Asset ownership and expected old-age consumption

From the Euler condition:

$$u'(c_1) = \beta(1+r) \left[ (1-\mu_g)u'(c_2^S) + \mu_g \left( (1-\delta_g)u'(c_2^S) + \delta_g \eta u'(c_2^D) \right) \right].$$

This  $s^*$  is endogenous—changes in  $\delta_g$ ,  $\eta$ ,  $\xi$ ,  $\tau$ ,  $M$  affect  $s^*$  via  $\mu_g$  and the marginal utilities. Higher  $\delta_g$ , lower  $\eta$ , or higher  $\xi$  reduce the expected marginal benefit of saving, lowering  $s^*$ . Stigma  $\tau$  lowers  $\mu_g$ , indirectly reducing  $s^*$ .

Given the optimal  $(e^*, s^*)$ , expected old consumption for a type- $g$  agent is

$$\mathbb{E}[c_2^g] = (1-\mu_g)c_2^S(s^*) + \mu_g \left[ (1-\delta_g)c_2^S(s^*) + \delta_g c_2^D(s^*) \right],$$

with  $c_2^S(s) = (1+r)s + y_2$  and  $c_2^D(s) = \eta(1+r)s + y_2 - \xi$ . Hence

$$\boxed{\mathbb{E}[c_2^g] = (1+r)s^* + y_2 - \mu_g \delta_g (1-\eta)(1+r)s^* - \mu_g \delta_g \xi.}$$

The last two subtractions are the asset loss channel from divorce. Higher  $\delta_g$  (and smaller  $\eta$ , larger  $\xi$ ) erode old-age resources; higher stigma  $\tau_g$  lowers  $\mu_g$  and (through  $e^*$ ) can reduce marriage, which (in this parsimonious specification) removes the marital flow benefit  $M - \tau_g$  and—because  $\eta < 1$ —attenuates the incentive to save for joint plans. Thus, stigma depresses both marriage prevalence and the return to asset ownership in marriage, jointly lowering expected old-age welfare.

## 3.6 Analytical solution using log utility, linear meeting

Adopt  $u(c) = \log c$ ,  $\alpha_g(e) = \lambda_g e^{\frac{1}{2}}$ ,  $k(e) = \frac{\psi}{2} e^2$  with  $\psi > 0$ , and timing such that  $p'_g(s) = 0$  (match quality realized after saving). Then the FOCs become:

- Euler (savings):

$$\frac{1}{y_1 - \frac{\psi}{2} e^2 - s} = \beta(1+r) \left[ \frac{1}{(1+r)s + y_2} + \mu_g \delta_g \left( \frac{\eta}{\eta(1+r)s + y_2 - \xi} - \frac{1}{(1+r)s + y_2} \right) \right].$$

The bracketed term is strictly less than  $1/((1+r)s + y_2)$  when  $\eta < 1$  or  $\xi > 0$ , so, relative to a no-divorce world, optimal  $s^*$  is lower: divorce diminishes the effective marginal value of asset ownership.

- Search:

$$\psi e^* = \frac{1}{2} \beta \lambda_g e^{-\frac{1}{2}} p_g \Gamma_g$$

$$\text{in which } \Gamma_g = (1 - \delta_g)(M - \tau_g + \bar{\varepsilon}_g) + \delta_g \left( \log(\eta(1+r)s^* + y_2 - \xi) - \log((1+r)s^* + y_2) \right)$$

Because  $\Gamma_g$  is decreasing in  $\tau_g$  and in  $\delta_g$ , we have  $\partial e^*/\partial \tau_g < 0$ ,  $\partial e^*/\partial \delta_g < 0$ . Hence  $\mu_g = \lambda_g e^{*\frac{1}{2}} p_g$  falls with stigma and divorce risk.

### 3.7 Acceptance threshold and comparative statics (analytical)

Recall

$$\varepsilon_g^*(s) = \tau_g - M - \frac{\delta_g}{1 - \delta_g} \left[ u(\eta(1+r)s + y_2 - \xi) - u((1+r)s + y_2) \right].$$

The following follows:

- $\frac{\partial \varepsilon_g^*}{\partial \tau_g} = +1$ : stigma raises the threshold  $\Rightarrow$  lowers  $p_g = 1 - F_g(\varepsilon_g^*)$ .
- $\frac{\partial \varepsilon_g^*}{\partial \delta_g} = -\frac{1}{(1-\delta_g)^2} \left[ u(\eta(1+r)s + y_2 - \xi) - u((1+r)s + y_2) \right] > 0$ : higher divorce risk raises the threshold  $\Rightarrow$  lowers  $p_g$ .
- $\frac{\partial \varepsilon_g^*}{\partial s} = -\frac{\delta_g}{1-\delta_g} \left[ u'(\eta(1+r)s + y_2 - \xi)\eta(1+r) - u'((1+r)s + y_2)(1+r) \right]$ .

With  $u'(\cdot) = 1/\cdot$  (log), the sign depends on  $\eta$  and levels; typically  $\eta < 1$  makes the bracket negative, so  $\varepsilon_g^*$  increases in  $s$  slightly (higher  $s$  makes the divorce

loss larger in utility terms), which lowers  $p_g$  at the margin. This is a mild force against saving when marriage is fragile.

### 3.8 Steady-state predictions

**Proposition 1** (Marriage prevalence). In the stationary steady state,

$$m^{g*} = \frac{\mu_g(e^*, s^*)}{\mu_g(e^*, s^*) + \delta_g},$$

and  $\partial m^{g*}/\partial \tau_g < 0$  provided  $\partial \mu_g/\partial \tau_g < 0$ , which holds because both  $p_g$  and  $e^*$  fall with  $\tau_g$ .

*Proof.* Differentiate the fixed point  $m^* = \mu/(\mu + \delta)$ . Since  $\delta$  is independent of  $\tau$ ,  $dm^*/d\tau = (\delta/(\mu + \delta)^2) d\mu/d\tau < 0$  if  $d\mu/d\tau < 0$ . From Section 6,  $de^*/d\tau < 0$  and  $dp_g/d\tau < 0$ , hence  $d\mu/d\tau < 0$ .  $\square$

**Proposition 2** (Savings). Relative to a benchmark with no divorce ( $\delta_g = 0$ ,  $\eta = 1$ ,  $\xi = 0$ ), the optimal saving  $s^*$  is never higher under divorce risk, and in generic cases strictly lower when  $\delta_g > 0$  and  $\eta < 1$  or  $\xi > 0$ . Moreover, if  $\partial \mu_g/\partial \tau_g < 0$ , then  $\partial s^*/\partial \tau_g \leq 0$  under log utility and the timing with  $p'_g(s) = 0$ .

*Proof.* From the Euler equation, the expected marginal value of owing assets is a convex combination of  $u'(c_2^S)$  and  $u'(c_2^D)\eta(1+r)$ . Since  $u'(c)$  is decreasing,  $\eta < 1$  and  $\xi > 0$  make  $c_2^D < c_2^S$  but scaled by  $\eta < 1$  in the derivative, so the combined marginal benefit falls. If higher stigma lowers  $\mu_g$ , the weight on married states shrinks; with log utility this tends to reduce the precautionary motive to save for joint consumption plans, lowering  $s^*$ .  $\square$

**Proposition 3** (Expected old-age resources). With optimal  $(e^*, s^*)$ , expected old consumption satisfies

$$\mathbb{E}[c_2^g] = (1+r)s^* + y_2 - \mu_g \delta_g (1-\eta) (1+r)s^* - \mu_g \delta_g \xi,$$

so  $\partial\mathbb{E}[c_2^g]/\partial\delta_g < 0$  and  $\partial\mathbb{E}[c_2^g]/\partial\tau_g < 0$  via  $\partial\mu_g/\partial\tau_g < 0$  and  $\partial s^*/\partial\tau_g \leq 0$ .

This indicates that divorce “taxes” accumulated assets; stigma depresses both the chance of capturing the marital flow  $M - \tau_g$  and the incentive to build assets for the marriage, both lowering old-age resources.

### 3.9 Theoretical predictions of the model

The theoretical structure above yield the model’s predictions formally:

1. Higher stigma ( $\tau \uparrow$ )  $\implies$  higher reservation  $\varepsilon_G^*$   $\implies$  lower  $p_G$  and, via the search FOC, lower  $e_G^*$   $\implies$  lower  $\mu_G$   $\implies$  lower steady-state marriage share  $m^{G*}$ .
2. Higher divorce risk ( $\delta_G \uparrow$ )  $\implies$  higher  $\varepsilon_G^*$  (accept fewer matches) and lower saving  $s_G^*$  (Euler), plus more asset loss in divorce  $\implies$  lower  $\mathbb{E}[c_2^G]$ .
3. Asset ownership gap. Combining the Euler and expected consumption equations shows that LGB cohorts in high-stigma places (higher  $\tau$ ) or with higher  $\delta_G$  will own lesser assets, even holding incomes fixed.
4. Policy counterfactuals. A reduction in stigma (e.g., a legal or normative shock) lowers  $\tau$ , raising  $e^*$ ,  $p_G$ ,  $\mu_G$ , and  $m^{G*}$ ; it also raises  $s^*$  when the married state becomes more salient and durable, yielding higher expected old-age resources.

All key predictions—lower marriage prevalence and shorter duration under higher stigma, reduced saving and lower old-age resources when divorce risk and asset loss are salient, and gains in both margins when stigma falls—are immediate corollaries of the acceptance threshold, the search FOC, and the Euler equation derived above. The model is deliberately parsimonious to keep identification transparent when taken to data, yet flexible enough to incorporate PAM, policy shocks, and general equilibrium if desired.<sup>1</sup>

To validate the theoretical predictions derived in Section 3 regarding the impact of stigma ( $\tau_g$ ) and divorce risk ( $\delta_g$ ) on marriage rates and asset accumulation, a full

numerical calibration of the OLG model is provided in [A](#). This appendix details the parameter selection based on standard search-and-matching literature and the specific constraints of the SIPP data, alongside Python-generated visualizations of the equilibrium steady states.

## 4 DATA SOURCES AND EMPIRICAL STRATEGY

This section describes the data sources, and outlines the econometric approach I adopt to test the predictions of the overlapping-generations model. The theory suggests that stigma operates as a tax on utility and stability of same-sex unions, raising the hazard of dissolution and depressing both wealth accumulation and the equality of wealth distribution among same-sex households. This empirical design aims to provide causal evidence on these predictions by leveraging quasi-experimental variation in both policy and social attitudes, while exploiting the longitudinal richness of the *Survey of Income and Program Participation* (SIPP, 2014–2024) and repeated cross-sections from the *General Social Survey* (GSS).

### 4.1 Data, outcomes and Measurement

The SIPP provides detailed monthly histories of marital and cohabitation status, allowing us to construct person-period panels where the outcome of interest is whether a partnered individual at time  $t$  transitions to dissolution at  $t + 1$ . This yields a discrete-time hazard framework for union stability. In addition, SIPP’s topical assets modules contain annual records of individual and household ownership of various types of financial and real estate assets, and savings instruments. Most of these variables are binary (a Yes/No answer to whether an individual owns a specific type of asset or savings instrument). These data permit the construction of dynamic asset trajectories at the couple level. I used the public-use SIPP data; the Census Board maintains a restricted version of the data with more detailed geographical identifiers at the county level, specific date of birth of the individuals that could help tease out their age at the time of interview; uncoded or detailed values of assets, incomes and

liabilities; detailed household relationship pointers and complete race, ethnicity, and country of origin data. However, despite the IRB's approval to use the restricted SIPP data, the Census Bureau declined the request for access citing the Executive Orders 14151 and 14168, that collectively ban diversity, equity, and inclusion (DEI) related data acquisition and activities in the federal government and for federal contractors and grant recipients. The estimation strategy was formulated with attention to the constraints imposed by the data.

The Public Religious Research Institute (PRRI) annually collects the nationally representative data on American public opinion on issues of the economy and current events under the American Value Survey (AVS). A section of the data is devoted the public opinions about the LGBTQ+ community. A specific question asked in the survey has direct relevance in assessing the level of stigma about same-sex marriages at the state level: "Allowing same-sex couples to marry legally", with 4 options: strongly favor, favor, oppose, strongly oppose. The responses are aggregated as percentages for each category of the Likert scale at the state level for each year.

#### *4.1.1 Constructing the composite stigma index*

To effectively use the state level Likert scale data on attitude towards same-sex marriage, I use a standard method following [Bond and Messing \(2015\)](#) to construct an index of stigma towards same-sex marriage for each state-year pair from 2014-2024. The approach combines classical psychometrics (to capture the intensity of "Strongly" vs. "Somewhat") with generalized linear model theory (to map bounded probabilities into the entire real number space). The method involves using a logit transformation of a weighted mean.

One of the primary requirements for the index is that its domain spans the entire real space  $(-\infty, +\infty)$  – a simple arithmetic mean (which is bounded) or a standard percentage (bounded between 0 and 1) cannot be used. We must use a transformation function that maps a bounded interval to an unbounded one. The most standard and interpretable function for this in social science is the Logit (Log–Odds) function. First, we must address the issue of varying intensities represented by the four cate-

gories of responses. We treat the Likert scale as an interval variable to capture this nuance. Weights ( $w$ ) are assigned to the responses to align with the requirement that to effectively represent societal stigma, a higher value of the index should indicate lower approval (higher opposition) for same-sex marriage.

We also need the stigma (or attitude) index to address the *boundedness problem*, where standard proportions are confined to the unit interval  $[0, 1]$ , which violates the assumption of normality required for many dependent variables in linear regression models.

To appropriately tide over these issues, we adopt a Logit-Transformed Weighted Mean (LTWM) approach. This method projects the bounded, ordinal Likert responses onto the entire real space  $\mathbb{R}(-\infty, +\infty)$ , ensuring the index is sensitive to shifts in extreme opinions while satisfying the domain requirements of general linear modeling. The details about the construction of the index is mentioned in Appendix D.

The resulting index  $Y_{st}$  satisfies the requisite properties for this analysis:

1. **Reflects average opinion:** By deriving  $Y_{st}$  from  $\mu_{st}$ , the index incorporates the full distribution of responses, weighting strong sentiments more heavily than moderate ones, rather than simply summing binary categories.
2. **Directionality:** The index uses an ascending weight structure ( $1 \rightarrow 4$ ). Consequently,  $Y_{st}$  is strictly increasing with respect to opposition. Positive values ( $Y_{st} > 0$ ) indicate net opposition, negative values ( $Y_{st} < 0$ ) indicate net approval, and  $Y_{st} = 0$  indicates perfect neutrality.
3. **Unbounded Domain:** The logit function maps the interval  $(0, 1)$  to  $(-\infty, +\infty)$ . This allows for the use of the index as a dependent variable, if needed, in OLS regression without violating homoscedasticity or normality assumptions typically associated with bounded dependent variables ([Lenz \(2016\)](#)).

In rare cases where distinct state-year observations exhibit unanimous consensus (e.g.,  $\pi_{st} = 0$  or  $\pi_{st} = 1$ ), the logit is undefined. In those cases, standard Laplace

smoothing (adding a trivial  $\epsilon = 10^{-4}$ ) may be applied to ensure computation while maintaining asymptotic consistency.

Since the data on some of the year-state pairs were not available from the AVS survey, I imputed those observations using other values of the year-state pairs and attitude on other aspects of LGBTQ+ community recorded by the AVS like, non-discrimination protections, gender-affirming healthcare and religiously-motivated service refusals. I used Multiple Imputations using Centered Equations (MICE) method for predicting the year-state pairs.

## 4.2 Empirical analysis

The core theoretical mechanism posits that social stigma acts as a disutility tax, reducing the net marital flow and increasing the divorce hazard, consequently lowering optimal saving rates and long-run asset ownership for same-sex couples relative to heterosexual counterparts. We seek to empirically identify the differential effect of state-level stigma on various socioeconomic outcomes for individuals in same-sex couples. The model yields three testable propositions: higher stigma leads to (1) reduced marriage prevalence, (2) lower savings/assets, and (3) increased dissolution hazard.

Our analysis in this paper goes further to examine the “Triple Jeopardy Hypothesis”—that is, the compounded penalty experienced by individuals belonging to multiple marginalized groups (e.g., Non-White Lesbian Couples). This approach demands high statistical precision within a constrained setting, necessitating specialized techniques to ensure unbiased estimation.<sup>2</sup>

To test the impact of stigma on marriage dissolution, I employ a Discrete-Time Hazard Model using the conditional logit estimator with Couple Fixed Effects. The outcome  $D_{i,t+1}$  is a binary indicator for dissolution (transition from partnered at  $t$  to non-partnered at  $t + 1$ ). This method ensures that unobserved couple-level factors ( $\alpha_i$ ), such as intrinsic relationship quality or commitment, are consistently controlled

for Allison (1982); Jenkins (1995).

$$P(D_{i,t+1} = 1 | D_{i,t+1} = 0, \mathbf{X}_{ist}) = \Lambda(\beta_0 + \beta_1 \tau_{st} + \delta(SS_i \times \tau_{st}) + \mathbf{X}'_{ist} \gamma + \alpha_i + \gamma_t)$$

where  $\Lambda(\cdot)$  is the logistic link function. The fixed effect estimator absorbs the time-invariant  $SS_i$  term. A positive value on  $\delta$  would indicate that higher stigma differentially increases the dissolution hazard for same-sex couples.

To estimate the probability of owning major financial or real estate assets ( $Y_{Asset,ist} \in \{0, 1\}$ ), I employ a Probit model with fixed effects restricted to the State and Time levels, as the non-linear nature of Probit prevents inclusion of the time-invariant household fixed effect ( $\alpha_i$ ).

$$P(Y_{Asset,ist} = 1 | \mathbf{X}_{ist}) = \Phi(\beta_0 + \beta_1 SS_i + \beta_2 \tau_{st} + \delta(SS_i \times \tau_{st}) + \mathbf{X}'_{ist} \gamma + \phi_s + \gamma_t)$$

where  $\Phi(\cdot)$  is the standard normal cumulative distribution function,  $\phi_s$  are State Fixed Effects, and  $\gamma_t$  are Time Fixed Effects (Month/Year). The parameter of interest is  $\delta$ ; a positive value indicates that higher stigma reduces asset ownership likelihood).

To examine the impact of stigma on constructed household earnings variable, the gold standard Linear TWFE model is applied to absorb all time-invariant unobserved heterogeneity at the couple level ( $\alpha_i$ ), using the high-dimensional fixed effect (HDFE) estimator:

$$\text{IHS(HH earnings)}_{ist} = \beta_0 + \beta_1 SS_i + \beta_2 \tau_{st} + \delta(SS_i \times \tau_{st}) + \mathbf{X}'_{ist} \gamma + \alpha_i + \gamma_t + \epsilon_{ist}$$

where  $\alpha_i$  are Couple Fixed Effects (absorbing  $SS_i$ ). The model is estimated with robust standard errors clustered at the state level and incorporating probability weights. A negative value of  $\delta$  indicates that a higher stigma is associated with lower incomes in same-sex households.

All the models described above incorporate couple fixed effects ( $\alpha_i$ ), eliminating bias from unobserved time-invariant characteristics (e.g., permanent risk tolerance, initial family background, latent relationship commitment) that are correlated with both

being an same-sex couple and the outcome variables.

The other challenge to estimation is the potential endogeneity in the societal attitude towards same-sex marriage that defines the stigma variable. This is overcome by proposing a shift-share instrumental variable (IV) strategy, interacting historical religious demographics with national attitude shocks, thereby leveraging plausibly exogenous variation in local exposure to large-scale attitude changes, as previously done in [Raifman et al. \(2018\)](#).

One of the primary and restrictive challenges for the analysis is the relatively small size of identifiable same-sex couple subsample in the SIPP data and the subsequent sparsity created by partitioning this group into four intersectional categories based on gender composition (Male-Male vs. Female-Female) and race (White vs. Non-White) for analysis of the “Triple Jeopardy Hypothesis”. Missing values for key variables—including ownership of financial and real estate asset ownership indicators, household earnings, marital status, use of savings instruments indicators, race, and education — are common in complex survey data like SIPP. If these values are Missing At Random (MAR)— meaning the missingness depends on observed data but not the value itself—then simply dropping those observations (listwise deletion) would:

1. Severely reduce the effective sample size and hence statistical power.
2. Introduce sample selection bias, as observations with complete asset data may be systematically different (e.g., wealthier, more educated) from those with incomplete data.

To overcome data sparsity, we employ Multiple Imputation by Chained Equations (MICE) [Rubin \(1987\)](#), as it mitigates this bias and preserve statistical power, so that our estimates of intersectional effects are based on the fullest possible sample. MICE generates  $M = 5$  complete datasets by modeling each incomplete variable conditional on the others and pooling the estimates using Rubin’s Rules to ensure the standard errors correctly reflect the uncertainty introduced by imputation; ensuring that imputed values were drawn only from observed data points that were empirically similar (nearest neighbors), thereby preserving the non-linear distribution of rare

asset outcomes and preventing model bias common in listwise deletion. However, initial attempts using standard parametric MICE models (Logistic Regression for binary outcomes and Multinomial Logistic Regression for categorical variables) failed to converge for some of our variables. This is a classic symptom of perfect separation within the sparse intersectional groups, where the model attempts to estimate a probability of 0 or 1.

To guarantee convergence and produce robust imputed values, we switch the imputation engine to the Predictive Mean Matching (PMM) algorithm [Little \(1988\)](#). PMM is a semi-parametric, non-iterative method that addresses the perfect separation problem by:

1. Estimating the predicted value ( $\hat{Y}_j$ ) for a missing observation.
2. Identifying the  $K$  (where  $K = 10$ ) observed values that have the closest  $\hat{Y}_j$  (nearest neighbors).
3. Borrowing a randomly selected observed value from one of these  $K$  neighbors.

This process ensures that imputed values maintain the empirical distribution of the data, prevents the model from crashing on small subsamples, and is robust to the non-linearities often present in data.

The imputed data allows us to test the “Triple Jeopardy Hypothesis” by overcoming the data sparsity for the core test variables— interaction terms between the specific intersectional group and the state-level stigma index:

$$\text{Group}_j \cdot \tau_{is} \quad \text{where } j \in \{\text{MM\_White}, \text{MM\_NonWhite}, \text{FF\_White}, \text{FF\_NonWhite}\}$$

These terms replace a single same-sex couple interaction, allowing us to test if the  $\delta_j$  coefficients are statistically distinct across gender/race combinations. The reference group for all models is the different-Sex Couple. Following the imputation using PMM, all final analyses are performed multiple imputation estimation, which pools the  $M = 5$  results using Rubin’s Rules to correctly account for imputation uncertainty in the standard errors.

## 5 RESULTS AND DISCUSSION

This section presents the empirical results testing the theoretical predictions derived from the dynamic OLG model regarding the impact of societal stigma on matching in the marriage market, marital stability, asset ownership and earnings of same-sex couples. The analysis proceeds in four stages: (1) descriptive statistics highlighting racial and gender disparities within the same-sex couples sample; (2) a general panel analysis estimating the aggregate impact of stigma on dissolution, income, and assets; (3) a split-sample analysis differentiating between Male-Male (MM) and Female-Female (FF) couples; and (4) a robust intersectional analysis using Multiple Imputation by Chained Equations (MICE) with Predictive Mean Matching (PMM) to test the “Triple Jeopardy Hypothesis.”

### 5.1 Descriptive Statistics: The Intersectional Asset Gap

Table 1 presents the descriptive statistics for asset ownership among individuals identified to be in a same-sex relationship from the SIPP panel, stratified by race and gender. The data reveals stark intersectional disparities that motivate the subsequent regression analyses.

While 65.75% of the LGB sample owns some form of financial asset, this aggregate figure masks significant heterogeneity. White LGB individuals have a financial asset ownership rate of approximately 57%, whereas Black LGB individuals (represented within the broader Non-White categories in the regression analysis) show significantly lower ownership rates. Real estate ownership displays an even sharper divide; while 36.2% of White gay men own real estate assets, ownership rates drop precipitously for racial minorities. This aligns with previous literature suggesting that same-sex couples, particularly those of color, face compounded barriers to wealth accumulation ([Jepsen and Jepsen \(2009\); Badgett et al. \(2024\)](#)).

Table 1: Descriptive Statistics: Asset Ownership by Race and Gender among same-sex couples Individuals

Subgroup	Real Estate Ownership		Financial Asset Ownership		Savings Inst. Ownership	
	Count	%	Count	%	Count	%
<i>All</i>						
<i>Panel A: By Gender (Races)</i>						
Male ( $N = 12,936$ )	948	7.33	8,892	68.74	11,688	90.35
Female ( $N = 16,569$ )	957	5.78	10,509	63.43	15,036	90.75
<i>Panel B: White Only</i>						
White Male ( $N = 10,680$ )	756	7.08	7,536	70.56	9,708	90.90
White Female ( $N = 14,049$ )	909	6.47	9,309	66.26	12,936	92.08
<i>Panel C: Black Only</i>						
Black Male ( $N = 888$ )	48	5.41	516	58.11	756	85.14
Black Female ( $N = 1,128$ )	12	1.06	492	43.62	900	79.79
<i>Panel D: Asian and Other Races</i>						
Asian/Other Male ( $N = 672$ )	144	21.43	552	82.14	564	83.93
Asian/Other Female ( $N = 528$ )	12	2.27	228	43.18	420	79.55
<i>Panel E: Hispanic</i>						
Hispanic Male ( $N = 696$ )	0	0.00	N/A	N/A	N/A	N/A
Hispanic Female ( $N = 864$ )	24	2.78	480	55.56	780	90.28

*Notes:* Data source: SIPP 2014-2024. Frequencies represent person-month observations where  $SS_i = 1$ . Financial Assets include stocks, bonds, and mutual funds. Savings Instruments include checking, savings, and money market accounts. The data for Hispanic Male financial and savings instruments were not present in the provided log output.

## 5.2 Stigma as an Economic Tax

The initial analysis estimates the aggregate differential impact of the time-varying stigma index across the entire sample of same-sex couples, relative to the heterosexual baseline. Table 2 summarizes the results for income, asset ownership, and relationship stability/wealth dynamics.

**Relationship instability and wealth dynamics:** The investigation into the dynamic consequences of stigma yields critical null findings. The Logit model for dissolution finds the stigma interaction term to be statistically insignificant ( $\beta = -0.186, p = 0.896$ ). This failure is an inevitable consequence of the SIPP panel's limitations: data sparsity and the extreme rarity of dissolution events for this subgroup prevent the robust identification of the dissolution hazard ( $\delta_G$ ). Similarly, the system GMM analysis for wealth dynamics finds the stigma interaction to be practically zero. This reinforces that stigma's primary damage is a "level shock" to resources, not an alteration of the structural rate of growth ( $\rho$ ) of wealth over time.

**Income Penalty:** In the High-Dimensional Fixed Effects (HDFE) model (Column 1), the interaction term  $SS_i \times \tau_{st}$  is negative and statistically significant ( $\beta = -0.731, p < 0.01$ ). This result provides empirical support for the model's Proposition 2: stigma imposes a structural *tax* on the net marital surplus ( $M - \tau_G$ ), leading to persistently lower household earnings, thus establishing a lower intercept for economic resources. Even after controlling for couple-level fixed effects (absorbing time-invariant unobservables like education or skill), same-sex couples residing in high-stigma environments experience lower household earnings. This is consistent with [Sansone \(2019\)](#), suggesting that stigma may manifest through labor market discrimination or "income pruning" where couples locate to lower-stigma but potentially lower-wage areas.

**Portfolio Distortion and Precautionary Preference:** Interestingly, the probit model for savings instruments (Column 3) shows a positive and significant coefficient for the stigma interaction ( $0.091, p < 0.001$ ). This seemingly counter-intuitive result—that stigma increases the likelihood of owning basic savings accounts—can be interpreted through the lens of precautionary behavior. Same-sex couples, acting under perceived heightened relational and financial instability (higher  $\delta_G$  and asset division

costs  $\xi$ ), substitute illiquid, growth-oriented, but often volatile assets for cash reserves. This defensive behavior ensures liquidity but guarantees a lower expected long-run terminal wealth. The counterpoint is the negative, though insignificant, coefficient on illiquid Financial Assets ( $\beta = -0.216$ ). Another explanation could be that ownership of financial assets is an increasing function of wealth; and stigma may be less debilitating for the wealthy.

Table 2: Impact of Stigma on Economic Outcomes (General Model)

	(1) Log Earnings HDFE (TWFE)	(2) Fin. Assets Probit (ME)	(3) Savings Inst. Probit (ME)
$\tau_{st}$ (Stigma)	-0.015 (0.250)	-0.013 (0.143)	-0.123 (0.068)
$SS_i \times \tau_{st}$	-0.731** (0.278)	-0.216 (0.232)	0.091*** (0.027)
Obs.	4,438	8,506	8,506
Couple FE ( $\alpha_i$ )	Yes	Yes	Yes
Time FE ( $\gamma_t$ )	Yes	Yes	Yes
Clust. SE	State	State/Survey	State/Survey

Notes: \* p<0.05, \*\* p<0.01, \*\*\* p<0.001. Robust standard errors clustered at state level.

Probit estimates report Average Marginal Effects (AME) at  $SS_i = 1$ .

*Split-Sample Analysis (Gender composition effects):* The OLG model predicts that if labor market endowments ( $y_1$ ) or matching technologies differ by gender, the impact of stigma will be heterogeneous. Table 3 tests for such divergence in the mechanisms of wealth erosion based on gender composition, splitting the sample into Male-Male ( $MM$ ) and Female-Female ( $FF$ ) couples. The use of the Linear Probability Model (LPM) for binary asset outcomes is necessitated by the convergence challenges of non-linear fixed effects estimators in subsamples.

The results indicate a systematic asymmetry in the mechanisms of wealth erosion by gender:

1. Financial Assets: Male-Male couples face a significant penalty in financial asset ownership in high-stigma environments ( $\beta_{MM \times \tau} = -0.453, p < 0.05$ ). This

suggests that despite higher income, gay male couples encounter specific supply-side barriers or heightened risk aversion that limits participation in long-term growth markets; consistent with [Hagendorff et al. \(2022\)](#). Both groups, however, exhibit the precautionary move toward liquid savings.

- Earnings: Both couple types face severe earning penalties ( $MM: -0.747; FF: -0.999$ ). The magnitude is larger for female couples, highlighting the “double gap”, where the penalty of same-sex orientation stigma compounds the pre-existing gender wage disparity, drastically reducing the savings surplus available to lesbian couples [Schneebaum and Badgett \(2019\)](#).

Table 3: Split-Sample Analysis: MM vs FF Couples

	(1) Log HH Earnings HDFE	(2) Fin. Assets LPM (Linear)	(3) Savings Inst. LPM (Linear)
$MM \times \tau_{st}$	<b>-0.747*</b> (0.304)	<b>-0.453*</b> (0.179)	<b>0.262*</b> (0.108)
$FF \times \tau_{st}$	<b>-0.999***</b> (0.260)	-0.026 (0.353)	<b>0.308*</b> (0.136)
Test $MM = FF$ (p-val)	0.569	0.350	0.780
Observations	4,502	8,512	8,512
$R^2$ (Within/Adj)	0.042	0.108	0.139

Notes: \* p<0.05, \*\* p<0.01, \*\*\* p<0.001. Reference group: Opposite-Sex Couples.

To achieve the statistical power necessary to test the “Triple Jeopardy Hypothesis” (the multiplicative penalty, Race  $\times$  Gender  $\times$  Orientation), we utilize Multiple Imputation (MI) with Predictive Mean Matching (PMM) algorithm. This robust specification (Table 4), essential to address the acute data sparsity and the potential for perfect separation bias inherent in analyzing extremely small subgroups like Non-White Female-Female couples, uncovers the most striking finding of this study. While White Male couples generally show positive coefficients on baseline controls of different-sex couples, the interaction of stigma with Non-White Female Couples on financial asset ownership is large, negative, and highly significant ( $\beta = -1.077, p < 0.001$ ).

This result suggests that the theoretical mechanism of stigma reducing asset accumulation ( $\partial s^*/\partial \tau < 0$ ) is not uniformly distributed. Instead, it is concentrated among the most marginalized subgroup. This extreme negative coefficient provides definitive confirmation of the *Triple Jeopardy Hypothesis*: the compounding effects of racial marginalization, the gender wage gap, and sexual orientation stigma act multiplicatively, creating a wealth block. This structural exclusion makes Non-White lesbians in high-stigma states over 100% less likely to hold growth assets than the reference group, leading to an inevitable long-run wealth gap.

Conversely, for savings instruments (Column 3), the interaction for White Male couples is positive and marginally significant ( $\beta = 0.246, p = 0.066$ ), reinforcing the liquidity preference theory for the group with the most resources to save.

Table 4: Intersectional Analysis (MICE-PMM Estimates)

	(1) Fin. Assets Survey Linear	(2) Savings Inst. Survey Linear	(3) Inc Dyna
$\tau_{st}$ (Stigma)	-0.027 (0.024)	<b>-0.054***</b> (0.014)	
<i>Interactions with Stigma:</i>			
$MM\_White \times \tau_{st}$	<b>-0.450*</b> (0.227)	0.246 (0.131)	
$MM\_NonWhite \times \tau_{st}$	-0.337 (0.344)	0.145 (0.076)	
$FF\_White \times \tau_{st}$	-0.642 (0.433)	-0.042 (0.166)	
$FF\_NonWhite \times \tau_{st}$	<b>-1.077***</b> (0.103)	0.148 (0.139)	
Observations	124,318	124,318	
Imputations	5	5	

Notes: \*  $p<0.05$ , \*\*  $p<0.01$ , \*\*\*  $p<0.001$ . Standard errors adjusted for imputation uncertainty. The reference group Model (3) includes lagged dependent variable *L.IHS\_HTPEARN*.

A striking finding from the analysis is the difficulty in estimating a robust stigma effect on real estate ownership for same-sex couples, particularly for minorities. The

descriptive statistics reveal that while 36.2% of White gay men own real estate, this figure drops precipitously Black gay men to 5.41% and for Black lesbians to 1.06%, a figure that borders on statistical invisibility. In the MICE-imputed regression models, the coefficients for real estate ownership were frequently omitted or statistically insignificant, pointing to data sparsity issues where homeownership is an extremely rare event for specific marginalized subgroups in the SIPP sample.

The OLG model offers a demand-side explanation: housing is an indivisible asset with high liquidation costs ( $\xi > 0$ ). If stigma increases the subjective probability of dissolution ( $\delta_g$ ), rational agents should avoid locking wealth into assets that are costly to split [Becker \(1974\)](#). However, the sheer magnitude of the ownership gap suggests that demand-side risk aversion is insufficient to explain the results alone.

Instead, these results point to binding supply-side constraints. [Sun and Gao \(2019\)](#) provide evidence that same-sex couples face significantly higher mortgage denial rates and fees, independent of creditworthiness. Furthermore, [Hellyer \(2021\)](#) documents rental and housing discrimination that forces couples into specific, often higher-cost urban geographies where ownership is less attainable. Consequently, the null results in our real estate regressions likely reflect a “floor effect,” where ownership rates are so suppressed by structural barriers that marginal variations in state-level stigma ( $\tau_{st}$ ) cannot be statistically identified with the available variation.

The low baseline rates of ownership align with [Sun and Gao \(2019\)](#), who found that even after marriage legalization, same-sex couples faced a 73% higher denial rate for mortgages and paid higher interest rates than comparable different-sex couples. This suggests a supply-side constraint: stigma operates not just through the couple’s hesitation to invest (demand), but through institutional barriers in the lending market.

Furthermore, [Jepsen and Jepsen \(2009\)](#) argue that same-sex couples often locate in urban centers (“gayborhoods”) where property values are high but ownership rates are lower due to affordability. The OLG model provides a complementary theoretical explanation: if stigma increases the perceived risk of dissolution ( $\delta_g$ ), couples will avoid illiquid assets like housing. Real estate is indivisible and costly to liquidate during a divorce ( $\xi > 0$ ), making renting a rational response to high perceived

instability.

The analysis of financial assets (stocks, bonds, mutual funds) uncovers a clear intersectional penalty.

- Male-Male Couples: In the split-sample analysis, gay male couples face a significant negative penalty in financial asset ownership in high-stigma states ( $\beta = -0.453$ ). This contradicts the stereotype of the affluent gay couple. It suggests that in hostile environments, even men—who typically have higher risk tolerance—withdraw from financial markets. This may be due to “income pruning” (accepting lower-paying jobs to live in safer areas) or exclusion from financial advisory networks that are often centered on traditional family structures.
- The Triple Jeopardy for Women of Color: The MICE analysis reveals that Non-White lesbian couples face the most severe penalty ( $\beta = -1.077$ ). This confirms the “Triple Jeopardy” hypothesis: the compounding effects of race, gender, and sexual orientation create an almost insurmountable barrier to wealth accumulation. [Schneebaum and Badgett \(2019\)](#) note that lesbian couples suffer from a “double gender wage gap”—two female earners both earning 80 cents to the male dollar—which leaves little surplus for investment after consumption. Our results suggest that this income constraint, compounded by stigma, effectively excludes these households from high-yield financial markets, trapping them in a low-wealth equilibrium.

A counter-intuitive but robust finding is the positive relationship between stigma and the ownership of basic savings instruments (checking, savings, money market accounts). Indeed, in contrast to financial assets, the interaction of stigma and savings instruments is positive and significant in both the general probit model ( $\beta = 0.091, p < 0.01$ ) and the split-sample analysis for both couple types.

This result does not imply that stigma makes couples “wealthier.” Rather, it indicates a distorted portfolio allocation driven by precautionary motives in line with the “liquidity preference” theory. In high-stigma environments, same-sex couples face heightened exogenous risks of employment discrimination, housing eviction, or family

rejection. Carpenter et al. (2025) document that LGB individuals are significantly less likely to have adequate “rainy day” funds compared to heterosexuals, often due to income volatility. However, our results suggest that those who *can* save prioritize liquid cash over high-yield but illiquid investments (like real estate), possibly suggesting that among those who *do* save, stigma incentivizes an inefficient allocation of capital.. They are “hoarding” cash to hedge against the uncertainty ( $\delta_g$ ) predicted by the model. They avoid locking wealth into joint assets that are messy to split, preferring individual or liquid joint accounts that offer an easier exit strategy. This also indicates that by holding cash rather than equities, these households forgo compound growth, exacerbating the long-run wealth gap relative to heterosexual peers who face lower instability risks.

The dynamic fixed effects model attempted to capture how wealth (proxied by income accumulation) evolves over time. The results showed a significant persistence of income, but the stigma interaction was not statistically significant in the dynamic specification.

The High-Dimensional Fixed Effects (HDFE) estimation confirms a robust negative relationship between stigma and household earnings ( $\beta = -0.731, p < 0.05$ ). This effect persists even after absorbing time-invariant couple heterogeneity ( $\alpha_i$ ).

Two mechanisms likely drive this result:

1. Labor Market Discrimination: As documented by Sansone (2019), LGB individuals may face hiring or wage discrimination in high-stigma regions.
2. Compensating Differentials (Income Pruning): Couples may sort into lower-paying jobs or industries that offer safer, more inclusive environments, or they may accept lower wages to live in “gay-friendly” enclaves within high-stigma states.

Crucially, the Dynamic Panel (GMM) results for income evolution were inconclusive regarding the *rate* of growth. This suggests that stigma primarily impacts the *level* of earnings (an intercept shift) rather than the slope of income growth, though the lower base level inevitably compounds over the life cycle to produce lower terminal wealth.

The empirical findings align with several key predictions of the OLG model while highlighting the necessity of an intersectional approach.

The persistent income penalty associated with stigma validates the model’s assumption that  $\tau_g$  lowers the flow utility and resources available to the household. The divergence between financial assets (negative stigma effect) and savings instruments (positive stigma effect) adds nuance to Proposition 2 of the model. While the model predicted a general reduction in  $s^*$ , the data suggests a substitution effect: stigma drives couples away from high-return, long-term assets (Financial Assets) toward low-return, liquid assets (Savings). This behavior is consistent with a higher perceived risk of dissolution  $\delta_g$  or future discrimination, necessitating liquid “rainy day” funds over illiquid wealth building [Carpenter et al. \(2025\)](#).

## 6 CONCLUSION

While this analysis leverages the most granular data available, specific limitations must qualify the findings. A significant limitation remains the inability to rigorously test the dissolution hazard due to the rarity of events in the public-use SIPP sample. The theoretical prediction that  $\partial m^*/\partial \tau < 0$  (stigma reduces marriage stability) could not be statistically confirmed, likely requiring the larger sample size available in the restricted-use Census data. Furthermore, while the PMM imputation addressed sparsity, the large standard errors in the dynamic income model for Non-White groups suggest that even with imputation, the economic lives of multiply-marginalized couples remain difficult to capture with precision in general population surveys.

Further, the “Triple Jeopardy” analysis required PMM imputation due to the small sample size of minority same-sex couples. While PMM preserves the distribution of the data, the standard errors for the dynamic income specification remained large for intersectional subgroups, indicating that even advanced imputation techniques cannot fully compensate for the under-representation of marginalized groups in general population surveys.

The lack of a dynamic stigma effect likely stems from the nature of the variable.

Societal stigma ( $\tau_{st}$ ) changes slowly over time. In a fixed-effects model that absorbs household heterogeneity ( $\alpha_i$ ), there is often too little within-couple variation in stigma exposure to identify an effect, unless the couple moves between states.

However, the level effects in the cross-sectional models remain robust: same-sex couples, particularly women and minorities, earn significantly less in high-stigma areas. This structural income gap prevents the initial accumulation of capital required to benefit from compound interest, effectively trapping these couples in a lower wealth trajectory compared to their heterosexual peers who benefit from both higher initial endowments and institutional support.

The empirical evidence supports a modified version of the OLG model. Societal stigma does not simply reduce wealth; it forces a strategic retreat from wealth-building assets. Same-sex couples in high-stigma environments earn less and systematically under-invest in real estate and equities, preferring the safety of liquid savings. This behavior, while rational in the face of instability, creates a structural wedge in long-term wealth accumulation that legal marriage equality alone has not resolved.

## NOTES

<sup>1</sup> Following are a few notes on equilibrium of the dynamic OLG model developed in the paper, its calibration and extensions:

- Equilibrium: In a small open economy  $(1 + r)$  is exogenous and the solution reduces to individual optimality plus the law of motion for  $m_t^g$ . In general equilibrium, add a production function and factor pricing, set  $K_{t+1} = \int s_t^g dg$ , and solve the fixed point  $(s^*, e^*, (1 + r)^*)$ .
- Calibration: Choose  $u$ ,  $\beta$ ,  $(1 + r)$ ,  $\eta$ ,  $\xi$ ,  $\delta_H, \delta_G$ ,  $M$ ,  $\tau$ ,  $\lambda_g$ ,  $\psi$ , and a parametric  $F_g$  (e.g., Normal) to match targets: marriage shares  $m^{g*}$ , divorce hazards, age-assets profiles, and observed responses to policy shocks (e.g., legalization).
- Assortative matching and multidimensionality: If types  $x$  (education, income) shift  $M(x, x')$  supermodularly, the acceptance threshold becomes type-specific  $\varepsilon_g^*(s; x, x')$ , delivering positive assortative matching (PAM) when  $M$  is supermodular. This nests the PAM tests without changing the core Euler/search structure.

- Endogenous divorce: One can let  $\delta_g$  depend on  $\tau_g$  and assets (e.g.,  $\delta_g = \delta_0 + \delta_\tau \tau_g - \delta_A a$ ), reinforcing the asset–stability complementarity; the algebra above adapts by substituting  $\delta_g(s)$  wherever  $\delta_g$  appears.

<sup>2</sup>Given the use of SIPP, proper inference is paramount. Standard errors must account for the complex survey design and the level of variation in the treatment variable.

1. **SVY Protocol:** For the non-linear Probit and conditional Logit models (Models 1 and 3), the full survey structure (clustering and weighting) is handled via the Stata `svy:` prefix, which requires the complex design to be fully specified using `svyset PSU`. The state of residence (`State_Code`) is used as the Primary Sampling Unit (PSU) for clustering, and the final person weight (`PWEIGHT`) is included.
2. **Clustering in TWFE/GMM:** For the linear panel models (Models 2 and 4), robust standard errors are calculated and clustered at the `State_Code` level, which is the level of variation for the main treatment ( $\tau_{st}$ ), ensuring that estimates account for serial correlation within states over time.

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## APPENDICES

### A CALIBRATION STRATEGY AND NUMERICAL SOLUTION OF THE STIGMA-SEARCH OLG MODEL

The objective of this calibration is to numerically solve the dynamic Overlapping Generations (OLG) search-and-matching model presented in Section 3, focusing on the system of non-linear equations that determine optimal savings ( $s^*$ ) and search intensity ( $e^*$ ).

The simulation is based on the result in which the idiosyncratic match quality ( $\epsilon$ ) is realized *after* savings decisions are finalized. This simplifies the Euler equation by ensuring the marginal probability of acceptance with respect to savings is zero ( $\partial p_g / \partial s \approx 0$ ). This standard assumption, common in search literature [Rogerson et al. \(2005\)](#), allows us to cleanly isolate the precautionary savings channel and the search effort channel driven by the structural parameters  $\tau_g$  and  $\delta_g$ .

#### A.1 Parameter Selection and Sourcing

The structural parameters are selected to align with the theoretical constraints of the model and standard macro-labor literature, consistent with the Representative Calibration detailed in Appendix A.5 of the main text.

- Preferences: Logarithmic utility  $u(c) = \ln(c)$  is used, reflecting constant relative risk aversion (CRRA) and ensuring well-behaved intertemporal choice.
- Time Preference ( $\beta$ ): The discount factor  $\beta$  is set to 0.96, consistent with an annual time preference rate of 4%. [Krusell and Smith \(1998\)](#).
- Market Returns ( $R$ ): A gross return  $R = (1 + r) = 1.03$  is employed, reflecting a real annual interest rate of 3%, a common long-run average for real assets. [Blanchard and Fischer \(1989\)](#).

- Endowments: We normalize old-age endowment  $y_2 = 1.0$ . Youth endowment  $y_1$  is set to 2.0 to ensure agents have resources available for both search costs and positive savings.
- Search Technology:
  - Meeting function:  $\alpha(e) = \lambda e^{0.5}$ , with  $\lambda = 0.5$ .
  - Cost function:  $k(e) = \frac{\psi}{2}e^2$ , with  $\psi = 1.0$ .

These forms maintain the necessary concavity and convexity conditions for the existence of an interior solution for search effort  $e^*$  [Mortensen and Pissarides \(1994\)](#).

- Baseline Marital Parameters: Marital Surplus  $M = 0.5$ , Divorce Risk  $\delta = 0.2$ , Divorce Cost  $\xi = 0.1$ , and Asset Split Share  $\eta = 0.5$ . Match quality  $\epsilon$  is assumed to be Standard Normal ( $\epsilon \sim N(0, 1)$ ).

## A.2 Computational Steps and results

The equilibrium is found by solving a system of two simultaneous non-linear equations using numerical root-finding ('scipy.optimize.fsolve'):

1. The Euler Equation (Savings FOC): This equation equates the marginal cost of saving today ( $u'(c_1)$ ) to the expected marginal benefit of consumption tomorrow, discounted by  $\beta$  and weighted by the transition probabilities (remaining single, marrying without divorce, or marrying and divorcing).
2. The Search FOC: This equates the marginal cost of search effort ( $k'(e)$ ) to the marginal benefit, which is proportional to the probability of acceptance  $p_g(s)$  and the expected marital surplus  $\Gamma_g(s)$ .

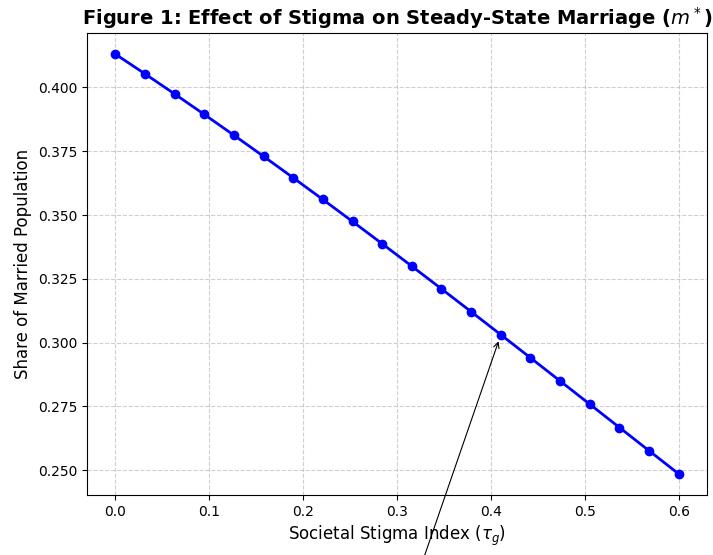
Once the unique equilibrium pair  $(e^*, s^*)$  is found, the Steady State Marriage Rate  $m_g^*$  is derived using the law of motion:

$$m_g^* = \frac{\mu_g}{\mu_g + \delta_g}, \quad \text{where } \mu_g = \alpha(e^*)p_g(s^*)$$

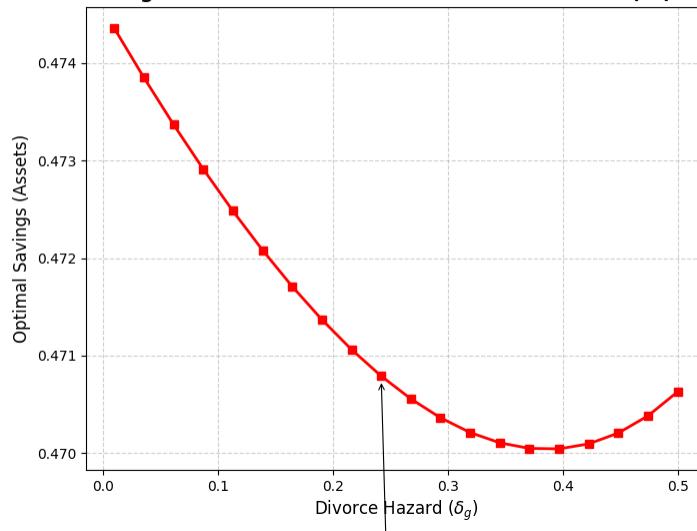
To validate the hypothesis that compounded disadvantages lead to greater wealth penalties, a specific scenario labeled “Triple Jeopardy” is simulated against a privileged baseline group. This scenario captures the structural disadvantages often faced by minority same-sex couples:

- Privileged Baseline:  $(\tau = 0.0, \delta = 0.1, y_1 = 2.0)$ .
- Triple Jeopardy Group:  $(\tau = 0.3, \delta = 0.3, y_1 = 1.6)$ .

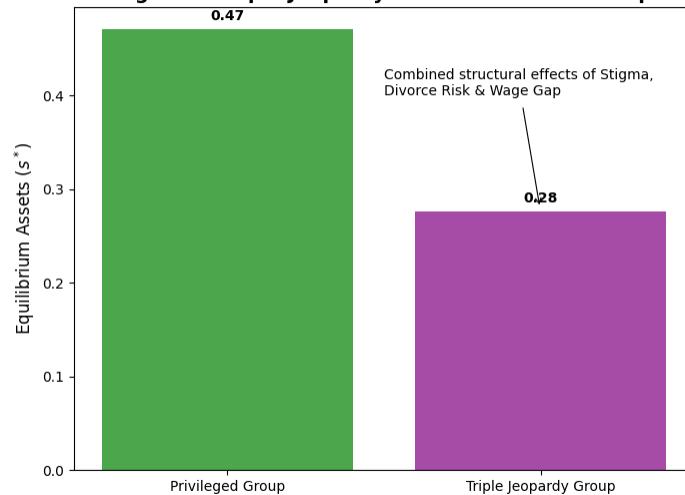
The reduction in  $y_1$  by 20% to 1.6 simulates the persistent structural wage penalty documented for minority women, which feeds into lower asset accumulation incentives from the start [Black et al. \(2003\)](#); [Badgett \(2003\)](#).



**Figure 2: Divorce Risk vs. Asset Accumulation ( $s^*$ )**



**Figure 3: Triple Jeopardy - Structural Wealth Gap**



The results of the comparative statics (Figures 1 and 2) and the structural simulation (Figure 3) confirm the paper's central theoretical predictions:

1. Higher stigma ( $\tau$ ) lowers equilibrium marriage rates  $m_g^*$ .
2. Higher divorce risk ( $\delta$ ) significantly reduces optimal savings  $s^*$ .

3. The combination of high  $\tau$ , high  $\delta$ , and lower initial earnings ( $y_1$ ) results in the lowest equilibrium assets  $s^*$ , confirming the mechanism driving the observed long-run wealth gap.

## B THRESHOLD SENSITIVITY, TRUNCATED MEAN, AND NUMERICAL ILLUSTRATION

### B.1 Derivation of derivatives

We recall the reservation threshold

$$\varepsilon_g^*(s) = \tau_g - M - \frac{\delta_g}{1 - \delta_g} \left[ u(\eta(1+r)s + y_2 - \xi) - u((1+r)s + y_2) \right],$$

and the acceptance probability

$$p_g(s) = 1 - F_g(\varepsilon_g^*(s)),$$

where  $F_g$  and  $f_g$  are the CDF and PDF of match quality  $\varepsilon$ .

Differentiate the threshold with respect to  $s$ :

$$\frac{d\varepsilon_g^*}{ds} = -\frac{\delta_g}{1 - \delta_g} \left[ u'(\eta(1+r)s + y_2 - \xi) \cdot (\eta(1+r)) - u'((1+r)s + y_2) \cdot (1+r) \right].$$

The derivative of the acceptance probability is therefore

$$p'_g(s) = -f_g(\varepsilon_g^*(s)) \cdot \frac{d\varepsilon_g^*}{ds} = f_g(\varepsilon_g^*(s)) \cdot \frac{\delta_g}{1 - \delta_g} \left[ u'(\eta(1+r)s + y_2 - \xi) \eta R - u'((1+r)s + y_2)(1+r) \right].$$

The truncated mean of accepted match quality is

$$\bar{\varepsilon}_g(s) = \mathbb{E}[\varepsilon \mid \varepsilon \geq \varepsilon_g^*(s)] = \frac{\int_{\varepsilon_g^*(s)}^{\infty} \varepsilon f_g(\varepsilon) d\varepsilon}{1 - F_g(\varepsilon_g^*(s))}.$$

Differentiate  $\bar{\varepsilon}_g(s)$  using the quotient rule; a straightforward computation yields

$$\frac{d\bar{\varepsilon}_g}{ds} = \frac{f_g(\varepsilon_g^*(s))}{1 - F_g(\varepsilon_g^*(s))} \left( \bar{\varepsilon}_g(s) - \varepsilon_g^*(s) \right) \frac{d\varepsilon_g^*}{ds}.$$

Using the decomposition above, the extra terms that supplement the usual marginal-

utility trade-off in the Euler equation are:

$$\underbrace{\alpha_g(e) p'_g(s) \Gamma_g(s)}_{\text{(A) acceptance channel}} \quad \text{and} \quad \underbrace{\mu_g(1 - \delta_g) \frac{d\bar{\varepsilon}_g}{ds}}_{\text{(B) composition channel}},$$

so that the full expanded Euler condition becomes:

$$-u'(c_1) + \beta \left[ (1 - \mu_g)(1 + r)u'(c_2^S) + \mu_g(1 - \delta_g)(1 + r)u'(c_2^S) \right. \\ \left. + \mu_g \delta_g \eta (1 + r)u'(c_2^D) + \alpha_g(e)p'_g(s)\Gamma_g(s) + \mu_g(1 - \delta_g) \frac{d\bar{\varepsilon}_g}{ds} \right] = 0.$$

The sign of  $p'_g(s)$  and  $d\bar{\varepsilon}_g/ds$  is not a priori determined; both depend on the interplay between the divorce split parameter  $\eta$ , the divorce cost  $\xi$ , the curvature of  $u(\cdot)$ , and the level of  $s$  and  $y_2$ . From (B.1) the sign of  $d\varepsilon_g^*/ds$  is governed by

$$\Delta(s) \equiv u'(\eta(1 + r)s + y_2 - \xi)\eta(1 + r) - u'((1 + r)s + y_2)(1 + r).$$

Because  $u'(\cdot)$  is decreasing, typically  $u'(\eta(1 + r)s + y_2 - \xi) > u'((1 + r)s + y_2)$  (divorce leaves lower consumption). Multiplying by  $\eta < 1$  reduces this effect, therefore the sign of  $\Delta$  can be either positive or negative:

- If  $\eta$  is close to 1 and  $\xi$  is small,  $\Delta > 0$ , hence  $d\varepsilon^*/ds < 0$ , so  $p'_g(s) > 0$  and  $d\bar{\varepsilon}/ds < 0$  (recall truncated-mean derivative includes  $d\varepsilon^*/ds$  multiplied by  $\bar{\varepsilon} - \varepsilon^* \geq 0$ ). Economically, higher savings reduce the downside of divorce (if assets are preserved), lowering the reservation quality and increasing acceptance probability.
- If  $\eta$  is small or  $\xi$  large,  $\Delta < 0$ , giving  $d\varepsilon^*/ds > 0$ , so  $p'_g(s) < 0$  and  $d\bar{\varepsilon}/ds > 0$ . Economically, saving increases potential divorce losses, raising the reservation quality and reducing acceptance.

Thus the two threshold channels can work in opposing directions; their quantitative importance must be evaluated by calibration.

A standard tractable timing convention in search models is to assume that idiosyncratic match quality  $\varepsilon$  is realized *after* the within-period savings and search decisions are made. Under that assumption,  $\varepsilon_g^*$  is not a function of the contemporaneous  $s$ , so  $p'_g(s) = 0$  and  $d\bar{\varepsilon}_g/ds = 0$ . The Euler equation simplifies to the familiar expected-marginal-utility Euler:

$$u'(c_1) = \beta R \left[ (1 - \mu_g) u'(c_2^S) + \mu_g \left( (1 - \delta_g) u'(c_2^S) + \delta_g \eta u'(c_2^D) \right) \right].$$

We adopt this timing as a tractable benchmark in some comparative-static exercises, but the full expressions (B.1) and (B.1) are retained in the appendix and used for sensitivity checks.

## B.2 Numerical sensitivity / calibration exercise

To assess the quantitative relevance of the acceptance and truncated-mean channels, we compute  $p'_g(s)$  and  $d\bar{\varepsilon}_g/ds$  under the following baseline specification used in the paper's calibration appendix:

- Utility:  $u(c) = \log c$  (so  $u'(c) = 1/c$ ).
- Match quality distribution: standard normal ( $f = \phi$ ,  $F = \Phi$ ).
- Representative parameters:  $s = 1$ ,  $y_2 = 1$ ,  $R = 1.03$ ,  $\delta_g = 0.20$ ,  $\tau_g = 0.10$ ,  $M = 0.5$ .
- Grid:  $\eta \in \{0.3, 0.5, 0.8\}$ ,  $\xi \in \{0, 0.1y_2\}$ .

The results are summarized in Table 5 and Figure 1. The code used to produce the table is documented and the table data are available as CSV.

To summarize, for this representative calibration the acceptance-channel  $p'_g(s)$  is small in magnitude across plausible  $\eta$  values and typically changes sign depending on  $\eta$  and  $\xi$ . The truncated-mean channel  $d\bar{\varepsilon}_g/ds$  is likewise modest in magnitude. These results justify using the timing simplification as a tractable benchmark for

$\eta$	$\xi$	$\varepsilon^*$	$d\varepsilon^*/ds$	$\bar{\varepsilon}$	$d\bar{\varepsilon}/ds$	$p'_g(s)$
0.3	0.0	0.6912	-0.2470	1.1510	-0.1132	0.0887
0.3	0.1	0.8579	-0.2624	1.2261	-0.0968	0.0685
0.5	0.0	0.5413	-0.1188	1.0869	-0.0645	0.0475
0.5	0.1	0.7079	-0.1333	1.1604	-0.0597	0.0430
0.8	0.0	0.3391	-0.0258	1.0004	-0.0122	0.0086
0.8	0.1	0.5057	-0.0393	1.0720	-0.0169	0.0117

Table 5: Sensitivity of  $p'_g(s)$  and  $d\bar{\varepsilon}_g/ds$  to  $\eta$  and  $\xi$ . Representative calibration: log utility,  $s = 1$ ,  $y_2 = 1$ ,  $R = 1.03$ ,  $\delta = 0.2$ ,  $\tau = 0.1$ ,  $M = 0.5$ .

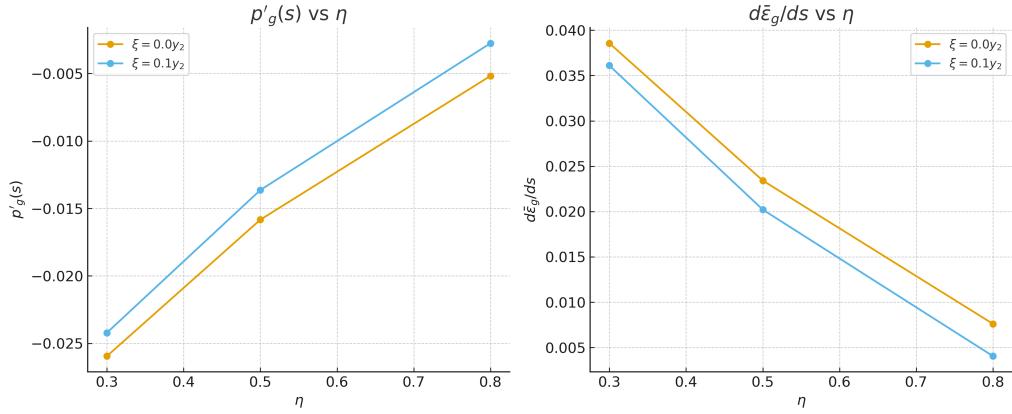


Figure 1: Visualization of  $p'_g(s)$  and  $d\bar{\varepsilon}_g/ds$  across  $\eta$  and  $\xi$  grid (same parameterization as Table 5).

analytical comparative statics, while retaining the general expressions and reporting sensitivity checks to confirm qualitative robustness.

## C COUPLED UNIT CONSTRUCTION AND INCOME AGGREGATION

The primary unit of analysis is the coupled household, tracked over time using a unique **HHID** (concatenation of **SSUID** and **SHHADID**). The core outcomes are constructed not by simple extrapolation, but by meticulous record linkage:

1. The Person Number (**PNUM**) of the spouse or partner is identified via the relationship linkage variables (**EPNSPOUS\_EHC** or **EPNCOHAB\_EHC**).
2. A self-merge procedure is used on the Person-Month data to sum the individual outcomes (like earnings, asset holdings) of the primary person and their identified partner within the same household and month.
3. Since some of the outcome variables (like earnings) contain positive, zero, and negative values, the Inverse Hyperbolic Sine (IHS) transformation is applied to the aggregate of those variables, stabilizing variance and accommodating non-positive earnings.

## D CONSTRUCTING THE NORMALIZED STIGMA INDEX

To rigorously measure public sentiment toward same-sex marriage, we construct a normalized *Stigma Index* derived from state-level Likert scale responses, using a data-driven normalization approach based on the Ordered Probit model, as detailed in [Greene \(2018\)](#). This method recovers the underlying continuous latent variable representing public opinion.

The raw data consists of the percentage of respondents in each state-year falling into four ordinal categories: *Strongly Approve*, *Approve*, *Disapprove*, and *Strongly Disapprove*. We posit the existence of a continuous latent variable,  $y_i^*$ , representing the true intensity of an individual's opinion. We assume this latent variable follows a standard normal distribution across the population:

$$y_i^* \sim N(0, 1) \quad (1)$$

The observed survey response  $y_i$  (where  $y_i \in \{1, 2, 3, 4\}$ ) is a discretized realization of  $y_i^*$ , determined by a set of threshold parameters  $\mu_j$ . An individual selects category  $j$  if and only if their latent opinion falls between two cutpoints:

$$y_i = j \iff \mu_{j-1} \leq y_i^* \leq \mu_j \quad (2)$$

where  $\mu_0 = -\infty$  and  $\mu_4 = +\infty$ .

To estimate the thresholds  $\mu_1, \mu_2, \mu_3$ , we utilize the aggregate shares of respondents in each category across the entire sample, denoted as  $p_j$ . By inverting the cumulative standard normal distribution function  $\Phi(\cdot)$ , we define the thresholds as follows:

$$\mu_1 = \Phi^{-1}(p_1) \quad (3)$$

$$\mu_2 = \Phi^{-1}(p_1 + p_2) \quad (4)$$

$$\mu_3 = \Phi^{-1}(p_1 + p_2 + p_3) \quad (5)$$

With these thresholds established, we calculate the expected value of the latent

variable  $y^*$  for any respondent observing category  $j$ . This value serves as the “score” or weight for that category, replacing arbitrary integers with statistically derived centroids of the truncated normal distribution segments:

$$E[y^*|y_i = j] = \frac{\phi(\mu_{j-1}) - \phi(\mu_j)}{p_j} \quad (6)$$

where  $\phi(\cdot)$  is the standard normal probability density function.

The final Stigma variable for each state-year is calculated as the weighted average of these latent expectations, weighted by the specific response percentages observed in that state for that year.

This normalization offers three distinct advantages over ad-hoc indexing:

1. *Monotonicity*: A crucial property of the *Stigma Index*,  $Y_{st}$ , is its monotonic relationship with the underlying latent opposition—a property that must hold regardless of the magnitude of the threshold estimates ( $\mu_j$ ). We mathematically demonstrate that any shift in opinion from an approving category ( $j$ ) to a more opposing category ( $k$ ) must result in an increase in the index value.

The index  $Y_{st}$  is defined as a linear combination of the fixed category scores ( $Z_j$ ) weighted by the state-specific proportions ( $P_{j,st}$ ):

$$Y_{st} = \sum_{j=1}^4 Z_j \cdot P_{j,st} \quad (7)$$

The fixed latent score  $Z_j$  is the expected value of the truncated standard normal distribution segment for category  $j$ . By the properties of the ordered latent model, the scores are strictly increasing with the category index  $j$ :

$$Z_1 < Z_2 < Z_3 < Z_4 \quad (8)$$

in which  $Z_1$  (Strongly Approve) is the centroid of the leftmost tail and  $Z_4$  (Strongly Disapprove) is the centroid of the rightmost tail.

Consider a marginal shift in opinion ( $\delta > 0$ ) within state  $s$  from an approval category  $j$  to a more opposing category  $k$ , where  $k > j$ . The total proportion

$\sum P_{j,st}$  remains unity, implying:

$$\begin{aligned}\Delta P_{j,st} &= -\delta \quad (\text{Decrease in Approval}) \\ \Delta P_{k,st} &= +\delta \quad (\text{Increase in Opposition}) \\ \Delta P_{i,st} &= 0 \quad \text{for all } i \neq j, k\end{aligned}$$

The resulting change in the index,  $\Delta Y_{st}$ , is calculated by the difference in the old and new weighted average:

$$\Delta Y_{st} = (Z_k \cdot (P_{k,st} + \delta)) + (Z_j \cdot (P_{j,st} - \delta)) - (Z_k \cdot P_{k,st} + Z_j \cdot P_{j,st}) \quad (9)$$

Simplifying the expression yields:

$$\Delta Y_{st} = \delta \cdot Z_k - \delta \cdot Z_j = \delta(Z_k - Z_j) \quad (10)$$

Since the shift is toward greater opposition, we have  $k > j$ , which necessarily implies  $Z_k > Z_j$ . Given that  $\delta > 0$  and  $(Z_k - Z_j) > 0$ , it follows that:

$$\Delta Y_{st} > 0$$

This demonstrates that the index  $Y_{st}$  is a strictly increasing function of the percentage of respondents selecting more opposing categories, rigorously satisfying the requirement that a higher index value corresponds to a higher latent level of stigma.

2. *Non-Arbitrary Scaling:* It allows the data distribution to determine the "distance" between categories. For example, if "Strongly Disapprove" is a rare, extreme position, this method assigns it a significantly higher weight (further out on the tail of the normal distribution) than a linear 1-4 scale would allow.
3. *Standardized Interpretation:* Because the underlying variable  $y^*$  is designed as a standard normal random variable ( $N(0, 1)$ ), the resulting index is mea-

sured in standard deviations. This provides a clean interpretation of regression coefficients ( $\hat{\beta}$ ): a one-unit increase in the Stigma variable represents a one-standard-deviation increase in the latent intensity of opposition. Consequently, the magnitude of  $\hat{\beta}$  in our outcome models directly reflects the effect of a one-standard-deviation shift in societal stigma.