Birth Mother Search for Adoptive Parents

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Abstract

We analyze decision-making under time pressure using a unique administrative dataset of mothers searching for adoptive parents at a large licensed adoption agency in the U.S. We establish that deadlines—specifically birth dates and gestational limits on abortion—drive search intensity and decision attention. To quantify the welfare implications of these constraints, we deploy a search model with endogenous deadlines. We use this framework to evaluate the welfare effects of the U.S. Supreme Court decision in the case Dobbs vs. Women's Health Organization to repeal national access to abortion. We find that the ruling fundamentally altered the option value of search, leading to significant welfare losses. These losses are not borne equally; they are concentrated almost entirely among minority mothers.

JEL classifications: J13, D91, J12, C78, D81, D83
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1 Introduction

One in twenty-five U.S. households with children has an adopted child, and five million American adults are adopted (Kreider and Lofquist, 2014; Adoption History Project, 2014). For non-relative adoptions, markets play a crucial role in matching mothers who consider adoption with families who want to raise a child but cannot have one or prefer not to.[1] Many actors are in this market, including licensed adoption agencies, attorneys and decentralized transactions aided by non-licensed professionals.[2] Licensed adoption agencies vet prospective parents, provide support and legal services related to the adoption process and show families to mothers searching for an adoptive family. These agencies maintain online platforms and, due to licensing and reporting requirements, increase the safety of the transaction for both sides of the market. Otherwise, transactions are conducted through decentralized searches with limited oversight.[3] Since personal and market-level conditions likely affect birth mothers' behavior, their interactions with these platforms can reveal their decision-making processes. We use birth mother visits to the online platform of a large licensed adoption agency in the U.S. to understand search behavior.

Our unique dataset allows us to complete two sets of analyses. First, we characterize the stylized patterns of search behavior, adoption and decision attention by birth mothers. Decision attention and framing effects on search behavior are tested through a platform policy change that effectively randomly assigned birth mothers menus of adoptive families. Second, we examine search model predictions that deadlines and changes in outside options affect the timing of search intensity by examining search behavior on the platform at natural

[1] Adoption markets are a classic example where social or ethical norms limit the use of money to facilitate exchange. People would find it inadmissible to buy and sell babies, or, in the terminology of Roth (2007), these transactions would be repugnant.

[2] Licensed adoption agencies provide comprehensive, regulated services throughout the adoption process—from mandated home studies and vetting to final placement paperwork—and must report their activities to federal authorities. In contrast, non-licensed professional (i.e. unlicensed adoption intermediaries, which are referred to as facilitators, consultants, brokers, marketers and advertisers) have no reporting requirements and offer only limited services, such as matching platforms, while the final legal work is typically handled by lawyers.

[3] See Baccara et al. (2014) for a description of these transactions.

deadlines and when options change. A birth mother with an unwanted pregnancy can place the child for adoption, keep the child or have an abortion. We gain valuable insight on this decision process by observing search behavior conditional on how close the birth mother is to giving birth when she starts her search (deadline effect) and on changes in access to abortion (change in outside option). Our data cover the period prior to and after the 2022 U.S. Supreme Court decision in the case Dobbs vs. Women's Health Organization.[4] This decision effectively shortened or eliminated the window over which mothers considering abortion or adoption could search for adoptive families, thus pushing mothers to search earlier in their pregnancy. We examine the effect of this change on search intensity and derive welfare implications for birth mothers.

Limited government regulation and privacy concerns contribute to the paucity of data on private domestic adoptions in the U.S. Little is known of behavior in the adoption market broadly (see Bernal et al., 2009, for an historical perspective), and even less on the decision-making of birth mothers. To our knowledge, our study is the first to establish patterns of birth mother search behavior in the private adoption market, how that behavior is affected by policy changes and impacts on their welfare. Previous research in this area has documented sex and race preferences of adoptive families (Landes and Posner, 1978) and examined decentralized matching (Baccara et al., 2014). More is known about public domestic adoptions through the foster care system (Child Welfare Information Gateway, 2025). These adoptions are different from those in the private market as they involve older children who have been removed from parental care and an agency serves as the representative of the child. The novelty of our study is our focus on the behavior of a birth mother deciding whether to place a child for adoption.

Through their online platform, our partner records detailed information on adoptive family and birth mother characteristics and behavior. Families are fully vetted and complete a comprehensive intake that includes their preferred characteristics of the adopted child.

[4]The Supreme Court decision eliminated the constitutional right to abortion in the United States and returned the authority to regulate or ban the procedure to individual states.

Subsequently, their profiles are posted on the platform. Birth mother inquiries, through an online form or phone call, by contrast, are kept private. They work with a social worker to identify families that would find the birth mother acceptable and initiate a possible match. In this setting, one side (the birth mother) makes the match proposal that the other must accept.

Because the birth mother effectively decides on the match, we focus on the behavior of birth mothers, not the adoptive families.[5] Our de-identified data on birth mother search is limited to their interactions with the agency. We do not observe their behavior prior to making an initial inquiry, nor their behavior, or child outcomes, after completing interactions with the agency. Our data provide a window into behavior, but it is not the complete decision process. Nonetheless, for all birth mothers who make an initial inquiry, we know: the age of the child at initial inquiry, the mother's age and race, her state of residence and whether she placed her child for adoption.[6]

Our main analysis examines the behavior of over 11,800 birth mothers over a five year period (2018-2023). Our first finding is a set of stylized patterns of behavior by birth mothers that conform with a search model with deadlines. Initial inquiries to the agency peak at the start of the third trimester and sharply decline thereafter through the child's birth date. The probability of placing a child for adoption steadily increases as the date of the child's birth approaches and plummets to roughly zero thereafter. These deadlines coincide with changes in mothers' choice sets: the date at which an abortion would be considered late-term (roughly the start of the third trimester) and the child's birth date. White and Hispanic mothers make initial inquiries earlier in their pregnancy than Black mothers who arrive close to the start of the third trimester. There is less heterogeneity in the pattern of placing a child for adoption by arrival times.

Our second finding is that mothers exhibit attention-driven biases, as reported in many

[5] Analyzing the adoptive family side is complicated by their potentially strategic preferences. Lacking the random variation in our data needed to account for this, we leave a full two-sided market analysis for future work.

[6] Almost all inquiries (98.4%) are by the birth mother alone (no information on the birth father).

other contexts (see Cattaneo et al., 2020; Goldin and Reck, 2020; Abaluck and Adams-Prassl, 2021, for review of evidence and analytical frameworks). This is notable as the stakes of the decision to place a child for adoption are extremely high, yet inattention still exists. We exploit a policy change that showed adoptive family profiles to birth mothers in an as good as random order to assess decision attention. We find that a mother is almost twice as likely to choose an adoptive family that is presented first. This framing effect becomes more pronounced as the mother is later in her pregnancy, especially for White and Hispanic mothers. This is analogous to the observation from the labor market literature that reservation wages decrease as unemployment insurance termination approaches (Moffitt, 1985; Katz and Meyer, 1990b,a; Card et al., 2007).

Our third finding is that mothers' search behavior responds to the available level of reproductive rights. The U.S. Supreme Court decision in the case Dobbs vs. Women's Health Organization altered mothers' search intensity. Post Dobbs, mothers arrived earlier in their pregnancy: the median age of the child at initial inquiry in states with trigger laws decreased by -15.2 days (s.e. 5.7) from a baseline of -111 days until birth. This change is more pronounced for Black mothers (-25.5 days, s.e. 8.2) and shifts their arrival times post-Dobbs to be on par with White mothers. This behavior is consistent with abortion being an alternative to adoption. These results confirm search patterns are not only due to unobserved heterogeneity among mothers visiting the platform. Indeed, mothers do react in intuitive ways to policy changes.

Finally, we build on these findings to inform a simple model of search with deadlines and derive the welfare implications of policy changes. Mothers' search behavior parallels that of unemployed workers searching for a job and facing the expiration of unemployment benefits. We take advantage of this similarity to derive sufficient statistics on the relative welfare effect of a policy that changes outside options. Because data on birth mother income is not available in our dataset, we estimate the implicit monetary welfare effect by comparing the relative impacts on arrival times from the Dobbs decision and post-COVID stimulus

payments. We note that our welfare estimate is based on a subpopulation affected by the court decision, i.e. women who have revealed they consider adoption as an option. It is unclear if these estimates are generalizable to other populations.[7] With that caveat, our analysis suggests that the welfare effect of abortion restrictions due to Dobbs, in our sample, is equivalent to a $1,166 decline in income. These welfare losses are concentrated on minority mothers.

Our first contribution is characterizing birth mother behavior as consistent with models of costly search with a deadline. This fits with the long tradition of conceptualizing fertility and reproductive decisions as dynamic problems (e.g. Hotz and Miller, 1993). The stylized patterns of search present new knowledge and resemble workers searching for jobs as the expiration date of unemployment benefits approaches. In that literature, the unemployment hazard rate drops sharply at that deadline (Moffitt, 1985; Katz and Meyer, 1990b,a; Card et al., 2007; Le Barbanchon et al., 2024), and changes in outside options, i.e. unemployment benefits, affect the timing of search (DellaVigna et al., 2017, 2022). This connection to search models allows us to derive welfare effects by comparing the effect of transfers to the effect of limits on abortion.

The second contribution is to the empirical literature on platforms for matching and assignment problems (see Arteaga et al., 2022; Kapor et al., 2024; Agarwal et al., 2019, 2021, for recent examples). To the best of our knowledge, we are the first to investigate behavior on a platform in the adoption market. Platforms like the one we analyze have been designed to increase the safety of transactions.[8] While there are gains from increasing the number of institutions on platforms (Kapor et al., 2024) and benefits from centralization (Agarwal et al., 2019, 2021; Baccara et al., 2020), the adoption market is one where no one dominant platform exists and decentralized transactions are nontrivial. This might be

[7] Recent research on the causal impact of denied abortion on mother seeking abortion in Colombia (Londoño-Vélez and Saravia, 2025) shows a negative impact on the health of the mother and their long-term outcomes.

[8] Other examples of platforms designed to increase safety include ride-sharing or house-sharing (i.e. Uber, Lyft, Airbnb, Vrbo).

a structural feature of the adoption market due to the strong deadline effects we report, and shown by Coey et al. (2020) in other contexts. Mothers in our setting are behavioral and tend to choose the first family they see (see Rees-Jones, 2017; Kapor et al., 2020, for evidence of biases in school choice). They may need nudges or suggestions to insure that final matches are close to first-best (see Belot et al., 2019; Rees-Jones, 2017, for an example of providing advice for job search). Alternatively, there might be gains from altering who is shown first to mothers as is done in position auctions (Haeringer, 2018, chapter 8, for a textbook exposition). Two-sided markets, such as our setting, may consider alternative structures to make transactions safe, especially for the most vulnerable, i.e., mothers and children.[9]

Our third contribution is to the literature on reproductive rights, fertility decisions and family formation. Our findings speak directly to the first-stage decision to place a child for adoption at birth when access to abortion services are restricted. Prior literature has examined a second-stage outcome, i.e. restricting access to abortion services on foster care placement. In this setting, restrictions result in a reduction in the number of abortions, an increase in overall fertility, and is associated with an increase in foster care entries and adoptions (Lindo et al., 2020; Fischer et al., 2018; Dench et al., 2024; Myers et al., 2025; Adkins et al., 2024; O'Donoghue et al., 2025; Guldi, 2008; Levine et al., 1999; Bitler and Zavodny, 2002; Gennetian, 1999; Medoff, 2008).

The magnitude, or even the existence, of an effect of abortion restrictions on private domestic adoption, i.e. not foster care adoption, is unclear. Findings from research outside of economics (Fuentes et al., 2023; Sisson, 2015) suggest that a link between abortion access and private domestic adoption might exist.[10] Our study directly examines the link between abortion restrictions and private domestic adoptions. We provide novel evidence that adop-

[9]Licensed adoption agencies, which provide the most safety in this market, are particularly important for this vulnerable population.

[10]The Turnaway Study—a qualitative, longitudinal study of a subset of women who sought abortions from 2008-2010—found that women seeking abortions and those considering adoption are largely distinct populations (Sisson et al., 2017); for instance, 86% of women denied an abortion reported they would not consider adoption (Foster, 2020).

tions and search intensity increase with abortion restrictions. These findings highlight the ramifications of current reproductive policies on an under-examined dimension of fertility decisions.

Finally, our paper contributes to the broader literature on child wellbeing and long run outcomes due to adoption (e.g., Sacerdote, 2002, 2011; Björklund et al., 2006), foster care (e.g, Baron et al., 2024; Doyle Jr and Aizer, 2018) and child neglect (e.g, Currie and Spatz Widom, 2010; Currie and Tekin, 2012). We provide first evidence of the linkage between abortion access and adoptions and that a mother's choice of an adoptive family is not always done with full attention to all options. This implies that a mother's decision is affected by ancillary characteristics of the choice set available to them. Future work will exploit this feature to assess how adoptive family characteristics affect children wellbeing and long run outcomes.

The remainder of the paper is structured as follows. Section 2 discusses adoption in the U.S., the private domestic adoption market and our partner adoption agency. Section 3 reports characteristics of birth mothers and adoptive families in our data. Section 4 presents stylized patterns of mothers' behavior: arrival times, probability of placing a child in adoption and decision attention. Section 5 evaluates the U.S. Supreme Court decision in the case Dobbs vs. Women's Health Organization on search behavior. Section 6 presents a decision framework for the birth mother's choice of adoptive family and derives predictions and welfare implications. Section 7 concludes.

2 Adoption

To contextualize our study, this section describes the U.S. adoption landscape, focusing on private domestic adoption through an agency, and introduces our partner agency.

2.1 Child adoption in the U.S.

In 2019, approximately 121,465 children were adopted in the United States, with another 123,000 awaiting adoption (Drumm et al., 2025). Together, these children represent 6.4% of all children born in the U.S. that year (National Vital Statistics System, 2020).[11] Adoption occurs through three channels: public domestic,[12] private domestic and familial,[13] and intercountry adoption,[14] which accounted for roughly 56%, 42%, and 2% of total adoptions in 2019, respectively (Children's Bureau 2022; Kohn et al. 2022; Bureau of Consular Affairs 2019). While public and intercountry adoptions were historically more common, legal issues and negative publicity have sharply reduced international adoptions, increasing the proportion of private domestic and familial adoptions (Mounts and Bradley, 2020).

Each adoption channel has distinct characteristics. In public domestic adoptions, a state agency with legal guardianship of a child—often obtained after an involuntary relinquishment of parental rights—transfers those rights to adoptive parents. In contrast, private domestic, familial, and intercountry adoptions involve the voluntary relinquishment of parental rights by the birth parent(s). Private and intercountry adoptions typically involve infants, whereas public domestic adoptions usually involve older children. Another key distinction across types of adoptions is geographic: private domestic, public domestic and familial adoptions occur when the birth parent(s) resides in the U.S. This paper focuses on private domestic and familial adoptions.

Private domestic and familial adoption includes three types: adoption of non-relatives, relatives, and stepchildren. The propensity to use an adoption agency—the setting for this

[11] The total number of children born in the U.S. in 2019 is 3,745,540.

[12] Public domestic adoption transfers the state's parental rights for a child in foster care to the adoptive parents. This occurs only when reunification with the birth parents is no longer feasible. The state first prioritizes placing the child with suitable kin. If no relatives are able or willing to assume custody, the child becomes available for adoption by an unrelated family.

[13] Private domestic and familial adoption is the voluntary transfer of parental rights from birth parents to adoptive parents, who may be relatives, stepparents, or other non-related individuals.

[14] Intercountry adoption is the adoption of a child from another country by a U.S. family. These adoptions often involve children from nations such as Russia, China, India, Ethiopia, and Guatemala (Bureau of Consular Affairs, 2019).

study—varies by type. Estimating the prevalence of each type is challenging because comprehensive national data is unavailable. Government reports often combine relative and non-relative adoptions, while survey and state court data suffer from inconsistent definitions and measurement practices (Child Welfare Information Gateway 2022). Our best estimate comes from the National Council for Adoption (NCFA), which reports approximately 25,500 private domestic non-relative adoptions occurred in 2022 (Drumm et al., 2025).[15] The adoption market itself is highly fragmented, with an estimated 1,050 entities placing adoptions.[16]

Our paper focuses on private domestic adoptions of non-relatives completed through an agency, a process driven by birth mothers searching for and selecting adoptive parents. Due to the aforementioned data challenges, the precise market size is uncertain. Given that private domestic adoption of relatives is a rare event,[17] we estimate that fewer than 25,000 private domestic adoptions of non-relatives (henceforth *private domestic adoptions*) occur annually via an agency.[18] Beyond completed adoptions, many more birth parents may consider this option when making fertility-related decisions.[19] These parents navigate a complex search and matching process to find suitable adoptive parents (see Moriguchi, 2012, for a extensive discussion of the different types of adoption in the U.S.).

[15]The current measure cannot accurately distinguish between relative and non-relative adoptions because it relies on imputed data from only a few states, hindering estimates of agency involvement in private adoptions. An alternative metric, the number of unrelated infant adoptions, combines both public and private cases. In 2014, this figure was estimated at 18,329.

[16]Estimated from the Heart Gallery of America's aggregation of U.S. Department of Health and Human Services data https://heartgalleryofamerica.org/adoption/state-links/. The primary source, the National Foster Care Adoption Directory, was unavailable (correspondence with Child Welfare Information Gateway, July 14, 2025).

[17]Private domestic adoption of relatives occurs when a child is voluntarily relinquished from one family member to another. Most familial adoptions, however, are either stepparent adoptions (estimated at 18,000–25,000 annually) or public domestic adoption as permanency plans for foster children.

[18]Based on the 2023 American Community Survey, we estimate that 21,999 children were placed for private domestic adoption in the U.S. in 2023. This finding is consistent with Sisson (2022), who reported a rate of 1 in 3,000 women placing a child for adoption annually.

[19]Based on our query data and assuming consistent inquiry rates across agencies, we estimate that roughly 360,000 birth parents consider private domestic adoption annually.

2.2 Private domestic adoption via an adoption agency

Private domestic adoption in the U.S. uses a decentralized system to match a birth parent (henceforth *birth mother*[20]) with an adoptive family to transfer parental custody. Licensed agencies must follow state-specific regulations and general rules preventing coercion or the sale of a child, and ensuring pre-placement agreements are non-binding.[21] This section describes historical trends in private domestic adoption and the general placement procedure for licensed agencies. The specific process of our partner agency is in Section 2.3.

Measuring the private domestic adoption market over time is difficult due to missing data. Voluntary state-level reporting existed from 1944 to 1975, but the lack of systematic data collection since then makes comparisons unreliable (Child Welfare Information Gateway, 2022). Early data show agency-led adoptions constituted 29% of all adoptions in 1951 and 38% in 1975 (Maza, 1984). Later estimates show private agencies conducted 4,235 adoptions across 12 states in 1987 and 3,514 across 14 states in 1992 (Flango, 1990; Flango and Flango, 1995). Data from the National Center of Social Statistics (NCSS) suggest that private domestic adoptions peaked in the 1960s-1970s before declining through the 2000s (Moriguchi, 2012). Modern surveys estimate an average of 20,000 to 25,000 private domestic adoptions annually between 2000 and 2023 (Child Welfare Information Gateway, 2022; Kohn et al., 2022; Drumm et al., 2025). A recent report suggests these adoptions made up 33% of the total in 2023, numbering 25,503 (Drumm et al., 2025). These estimates, particularly from the NCSS, should be interpreted cautiously, as they rely on national imputations from voluntary state data and may be inflated.

[20] Almost all birth mothers (98.4%) with our partner agency do not list a birth father, leaving only the birth mother to interact with the adoption agency.

[21] The Interstate Compact on the Placement of Children (ICPC) governs U.S. adoptions across state lines, ensuring uniform protection for children. In an adoption, a licensed agency or attorney legally handles the placement. This differs from facilitation, where unregulated entities act only as matching services and must defer the legal placement to an agency or attorney (Baccara et al., 2014). Because many states prohibit adoption facilitators (Child Welfare Information Gateway, 2020), i.e. Arizona, Connecticut, D.C., Delaware, Georgia, Illinois, Iowa, Kansas, Maine, Massachusetts, Minnesota, Montana, Nebraska, Nevada, New Mexico, New York, North Dakota, Ohio, Oklahoma, Oregon, West Virginia, and Wisconsin, our focus on private adoption agencies, which operate nationwide, is broadly generalizable.

Prospective adoptive families typically begin the process by contacting a licensed agency, completing an application, and paying a fee. The application captures the family's characteristics and their preferences for a potential match. If the family meets the agency's standards—which may consider the number of parents, marital status, age, sexual orientation, criminal record, income, and residence—the process begins. All adoptive families must pay for and pass a home study, a state-mandated prerequisite for gaining parental rights. A home study verifies the family's parental fitness and assesses the home environment to ensure it meets state standards for guardianship.

After completing the assessment and home study, the family creates a profile and joins the agency's pool of prospective parents. The matching process varies by agency. Most commonly, the birth mother selects an adoptive family from a pool of profiles, which may be curated by the agency based on matching preferences. Less frequently, the process is reversed, with adoptive families selecting from birth mother profiles. Wait times for a match can range from months to years, depending on factors like the number of birth mothers, the family's state of residence, the stringency of their preferences, their characteristics, and their budget.

The process for birth mothers is similar. Agencies gather their characteristics and preferences, as well as information about the child. A social worker often guides the birth mother through her options. Accommodations, such as stipends for rent, healthcare, and groceries, may be provided by the agency or prospective adoptive parents, but these are non-binding. To reduce attrition after significant investment, agencies often provide birth mothers with resources for alternatives to adoption.

When selecting a family, a birth mother may consider their budget, age, race, marital status, location, and desired adoption conditions (e.g., open vs. closed).[22] Most birth mothers contact an agency during pregnancy or immediately after birth, though they can do

[22]The terms "open" and "closed" adoption describe the post-placement relationship between the birth mother and the adoptive family. This relationship exists on a spectrum, ranging from ongoing contact (e.g., calls, visits) in an open adoption to the sealing of all records to prevent interaction in a closed one.

so at any stage. A match can occur anytime after intake, but the adoption is only finalized after the child is born, according to procedures that vary by the home states of the birth mother and adoptive family.

2.3 Adoption process with partner adoption agency

We partnered with a large U.S. licensed adoption agency, which follows the general procedure from Section 2.2.[23] We highlight several key details. Both adoptive families and birth mothers find the agency through conventional means (e.g., internet search, referrals) and contact them by phone or online form. Adoptive families submit an application and a fee, provide detailed information, and either begin a home study with the agency or provide one completed elsewhere. After a full vetting and approval, the family creates a profile and is added to the pool of waiting families, where they remain until selected by a birth mother.

A birth mother can browse family profiles on the agency's website before making contact. She can initiate contact in three ways: a general online inquiry, an inquiry for a specific family, or a phone call. Unlike adoptive families, birth mothers initially provide minimal information, such as contact details, basic demographics, and the child's age or due date. Those who inquire via a general form or phone call immediately receive a "Welcome Email" with a list of 20 waiting families compatible with the child's sex and race and interstate legal requirements.[24] This email is the only communication universally sent to all birth mothers who inquire by general form or phone call. A social worker then contacts the birth mother to help her find a suitable family. While all birth mothers receive the initial email, additional profiles are sent only upon request. Birth mothers can also browse all online profiles independently on the agency's website.

When a birth mother selects a family, they are provisionally matched in what is called an

[23]To test the generalizability of our partner agency's process, we contacted five large U.S. adoption agencies. We found that most had comparable websites, resources, and adoptive family profiles. Crucially, they offered similar tools for birth mothers to search for and filter potential families. Three of the five agencies responded and provided their informational materials for birth mothers.

[24]In approximately 6% of cases, a birth mother receives fewer than 20 profiles. This limited selection often results from a combination of the adoptive families' preferences and legal restrictions on interstate adoption.

"adoption opportunity," and the adoptive family's profile is removed from the active pool.[25] From this point, the birth mother has three options: (1) proceed with the adoption, (2) decline the match and return to the pool to select another family, or (3) decline the match and exit the process.

After being selected, adoptive families face two scenarios. If the birth mother matches their stated preferences, they can either proceed with the adoption process or exit the agency entirely. Crucially, if the birth mother fits their preferences, the family cannot reject the match and return to the waiting pool. If the birth mother does not match their stated preferences, the family can choose to proceed with the match or reject it and re-enter the waiting pool. This process functions as an assignment problem where birth mothers act as choosers from a choice set that varies with their arrival time.[26]

3 Adoption data

3.1 Description of data

Private domestic adoption is difficult to track due to data confidentiality. Our study uses a novel, de-identified dataset from our partner adoption agency, containing administrative records on birth mothers and adoptive families. This unique dataset allows for a detailed examination of the birth mother's decision-making process. Our partner operates nationwide, provides services throughout the entire adoption process, from initial inquiries, to matching a mother with a family to assisting with final transfer of parental rights, and collects detailed preference data from both birth mothers and adoptive families.

The available data on birth mothers and adoptive families differs. Adoptive families provide detailed household information, whereas data for birth mothers who only make an

[25] While an adoption agency's legal role differs between licensed states (creating a match) and unlicensed states (facilitating a mutual choice), the process and services are functionally indistinguishable for our research.

[26] Because birth mothers sequentially select from a constrained set of available families, truthfully stating their preferences is a dominant strategy.

initial inquiry is limited to basic demographics, such as age, race and sex of the child and birth mother's age and sex. Birth mothers who proceed to adoption placement provide complete demographic and preference information. We do not have information on birth mothers who exit the agency or on birth mothers' behavior outside their interactions with the agency. Our analysis focuses on birth mothers who first contacted the agency between August 1st, 2018, and June 30th, 2023. This period was selected because a process change on August 1, 2018 introduced a quasi-random ordering of adoptive family profiles in welcome emails, a feature central to our research design, and June 30, 2023 is one year after the U.S. Supreme Court Dobbs decision that restricted abortion access.

Figure 1 illustrates the adoption process.[27] Of the approximately 17,500 birth mothers who made an initial inquiry, 95% did so via the general online form or a phone call, all of whom received a welcome email. From these inquiries, 13% (n=2,342) proceeded to discussions of adoption, which result in either a match finalization or exiting the agency. Of these discussions, 17% (n=400) fail, and the mother enters a discussion with a new family or exits the agency. Ultimately, 6.2% of all initial inquirers (n=1,084) finalized an adoption placement. Our analysis focuses on three main outcomes: the child's age at initial inquiry, the matches or adoption opportunities that end in adoption placement and birth mother attention in the matching process

We restrict the sample to birth mothers who receive a welcome email, i.e. mothers whose initial contact was through the general online form or a phone call. This restriction ensures that all mothers in our sample received a welcome email with a quasi-randomly ordered list of adoptive family profiles, which we use to measure decision attention. This restriction also avoids potential bias from mothers who inquire about a specific family. We also exclude mothers who enter the agency with a chosen adoptive family, as their process did not involve a search. We further limit the sample to a mother's first inquiry for a given child, children under 300 days old and mothers with a listed expected due date and an active

[27]Figure 1 includes all birth mother inquiries to our partner agency during the sample period.

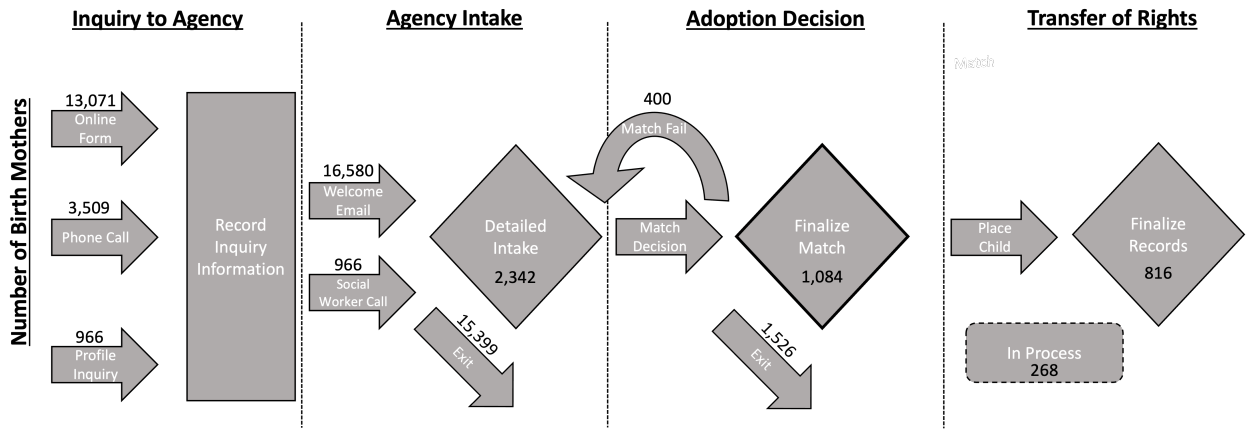


Figure 1: Adoption Process for Birth Mothers

Notes: The figure shows the four main stages of the adoption process, tracking the number of birth mothers and attrition from August 1, 2018, to June 30, 2023. Inquiry to Agency includes inquiries via online form, phone, or a specific family profile. Agency Intake shows mothers who complete a detailed form, while Adoption Decision tracks those who finalize a match or exit. Our primary outcome of interest relating to adoption placement is captured in the bold diamond Finalize Match. Transfer of Rights shows mothers who have completed the legal transfer; some are still in process because the child is not yet born or due to varying state laws.

email account.[28] This results in 12,838 unique mothers and 879 final matches.

For our analysis on search in Section 4, we make additional restrictions to our outcome measurement. To ensure consistent measures of search across individuals, we focus only on formal searches when defining our outcomes (652 final matches). A formal search includes search behavior and matches that are tracked through the agency. We exclude search activity conducted outside of these formal channels to maintain consistent tracking of behavior and outcomes.[29]

3.2 Description of Birth Mothers and Adoptive Families

Table 1 provides descriptive statistics for birth mothers. On average, birth mothers are 26 years old and make their initial inquiry about three and a half months (-110.8 days) before

[28] 0.67% of mothers make more than one inquiry, i.e. they appear in our data for more than one child.

[29] Examples of non-formal searches include instances where a birth mother independently searches for and matches with adoptive family profiles on partner or non-partner websites without working through her assigned social worker, or when matches occur through personal networks or direct contact outside the agency's tracking system.

Table 1: Birth Mother Matching Statistics by Race

	Total		Black		Hispanic		White		Other	
	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean
BM Age Shown	10,033	26.244	2,621	24.942	1,575	25.474	4,998	27.095	820	26.746
		(6.377)		(5.669)		(6.082)		(6.605)		(6.786)
BB Age Shown	12,838	-110.802	3,369	-83.668	1,988	-118.179	6,376	-123.540	1,079	-108.089
		(105.736)		(113.089)		(101.176)		(98.959)		(112.341)
Match	12,838	0.068	3,369	0.058	1,988	0.060	6,376	0.080	1,079	0.055
		(0.253)		(0.233)		(0.237)		(0.271)		(0.227)
BB Age Match	879	-31.804	194	-22.536	119	-31.597	507	-37.065	59	-17.492
		(57.928)		(61.522)		(44.681)		(58.555)		(59.093)
Time to Match	879	52.276	194	47.840	119	45.496	507	55.633	59	51.695
		(44.835)		(39.106)		(44.778)		(46.414)		(47.004)

Notes: Standard deviation in parentheses for means. Age and time is in days. A negative value for age represents days until expected due date. BB = Baby, BM= Birth mother. To avoid outliers, the sample is restricted to birth mothers whose child is less than 300 days old. 26 birth mothers did not have a race listed.

their due date. Approximately 7% finalize an adoption. The mutual selection process with a family typically begins about one month before birth and lasts 52 days.

The table also reveals significant variations by race. Black birth mothers, on average, inquire later in their pregnancy (-83.7 days) compared to White (-123.5 days) and Hispanic (-118.2 days) mothers. While White birth mothers are more likely to finalize an adoption (8.0%), their time to finalize a match is slightly longer (55.6 days).

Table 2 compares the characteristics of birth mothers who did and did not place a child for adoption. Those who finalize an adoption are, on average, significantly older by 1.4 years ($p<0.001$) and inquire 28.7 days later in their pregnancy ($p<0.001$). They are also 4.5 percentage points less likely to be Black ($p=0.003$). We find no significant differences in marital status ($p=0.214$) or the proportion of Hispanic mothers ($p=0.093$), although marital status is reported on a smaller sample.[30]

Table 3 details the characteristics of adoptive families in our sample. The average parent is 37 years old, and most families are White (93%) and heterosexual couples (90%). Regarding preferences for a child's race, 50% of families are open to adopting a Black child, compared to 83% for a White child and 73% for a Hispanic child, consistent with Baccara

[30]The characteristics of birth mothers in our sample who place a child for adoption align with those reported by other agencies (Sisson, 2022), suggesting our sample is representative of the broader population.

Table 2: Birth Mother Summary Statistics by Matching Status

	Matched		Did Not Match		
BM Characteristics	N	Mean	N	Mean	Difference
Age	879	27.523	9,154	26.121	1.402
		(6.180)		(6.383)	(0.225)
Single	158	0.854	1,215	0.888	-0.034
		(0.354)		(0.315)	(0.027)
Black	879	0.221	11,933	0.266	-0.045
		(0.415)		(0.442)	(0.015)
Hispanic	879	0.135	11,933	0.157	-0.021
		(0.342)		(0.363)	(0.013)
BB Age Arrived	879	-84.081	11,959	-112.766	28.685
		(74.563)		(107.412)	(3.687)
BB Age Matched	879	-31.804	-	-	-
		(57.928)			

Notes: Standard deviation in parentheses for means, standard error in parentheses for differences. BB = Baby. To avoid outliers, the sample is restricted to birth mothers whose child is less than 300 days old. 26 birth mothers did not have a race listed.

et al. (2014). However, unlike that study, 98% of families state no preference for the child's sex. The adoptive families in our sample are significantly wealthier than the average U.S. household, with a median income of $162,000 (average $194,424) compared to the 2021 U.S. median of $70,784 (Semega and Kollar, 2022). During the sample period, each family's profile was shown to birth mothers an average of 195 times.

Table 3: Adoptive Family Descriptives

	N	Mean
AP1 Age	1,796	37.610
		(5.475)
AP2 Age	1,796	36.863
		(5.179)
AP1 Black	1,790	0.023
		(0.150)
AP2 Black	1,795	0.020
		(0.140)
AP1 Hispanic	1,790	0.047
		(0.212)
AP2 Hispanic	1,795	0.059
		(0.236)
AF Preference for Black child	1,792	0.515
		(0.500)
AF Preference for White child	1,792	0.831
		(0.374)
AF Preference for Hispanic child	1,792	0.727
		(0.446)
AF Preference for Sex of Child	1,796	0.020
		(0.140)
AF Same Sex	1,796	0.101
		(0.301)
AF Budget	1,796	43,759.049
		(24,667.044)
AF Salary	1,661	194,424.328
		(135,259.525)
Times Profile Shown	1,796	194.821
		(179.824)

Notes: Standard deviation in parentheses. AP1 = Adoptive Parent 1, AP2 = Adoptive Parent 2, AF = Adoptive Family. AP 1 is the male in heterosexual couples. AP 2 is the female in heterosexual couples. Sample has 6 single AFs. If a gender preference is stated, females are preferred 69.4% of the time.

4 Patterns of mothers' search behavior

We present stylized patterns of birth mothers' search behavior in four key areas: (1) arrival time (i.e. child's age at mother's initial inquiry), (2) search and the probability of placing a child for adoption, (3) mother decision attention and (4) costly search with a deadline.

4.1 Arrival time

We use the time remaining in pregnancy at initial inquiry to the agency as an indication of search intensity.[31] Women learning of an unwanted pregnancy have to decide between three options: keep the child, place the child for adoption or have an abortion. Finding a suitable adoptive family might take several attempts, and securing an early agreement could help reduce the costs associated with carrying a child to term. Thus, arrival time to the agency affects the options available for the mother, i.e. delay may make abortion more risky or illegal.

The average age of the child at arrival is roughly three and half months prior to the due date, i.e. -110 days (SD 106 days) (Table 1), with Black mothers arriving later and White and Hispanic mothers arriving earlier in their pregnancies. The difference between Black mothers and either White or Hispanic mothers is statistically significant (p-value $<$ 0.0001), as is the difference between Hispanic and White mothers (p-value $=$ 0.0353). Search duration, as measured by the difference between a mother's initial and final contact with the agency, is shorter for those who arrive later in their pregnancy ($\rho = -0.0537$, p-value < 0.0001). Also, mothers who arrive late in their pregnancy are sent fewer adoptive family profiles ($\rho = -0.0205$, p-value $= 0.0213$). Intuitively, if mothers believe the pool of adoptive

[31] Time to a deadline has been used previously as a measure of search intensity, e.g. in airline ticket purchases prior to advance purchase deadlines (Hotle et al., 2015), football game tickets (Waisman, 2021), on eBay (Blake et al., 2016). Coey et al. (2020) demonstrate that heterogeneous deadline effects on eBay can explain the co-existence of auction and posted prices. In our setting, heterogeneous effects are due to birth dates.

families is finite, arriving early increases the chances of finding a suitable family.[32]

4.2 Search and probability of adoption

To examine how search behavior and the probability of adoption interact, we exploit the structure of our data to construct menus. A menu is the number of adoptive family profiles the agency sent to the mother. We do not observe the profiles a mother may have considered on her own, thus, we consider this analysis exploratory

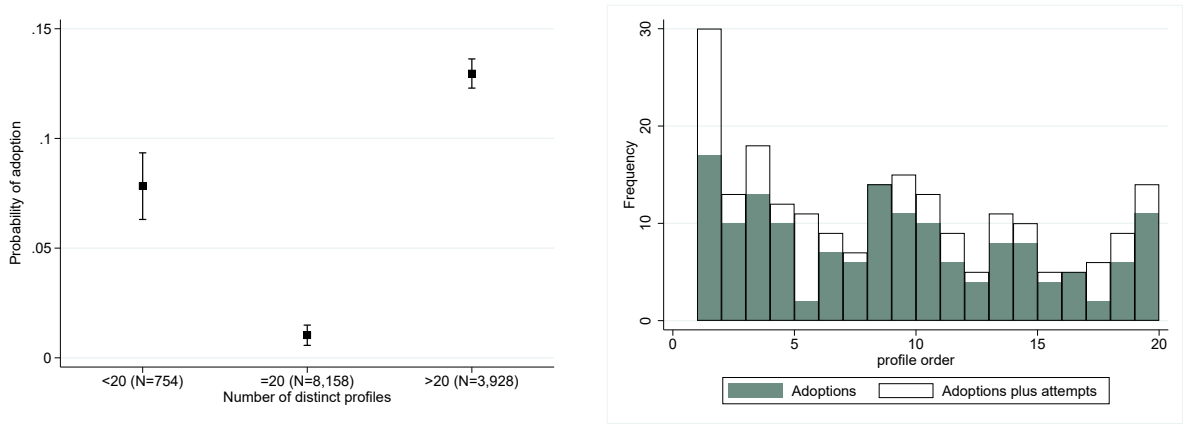
Figure 2, Panel (a), shows the probability of adoption as a function of the size of the menu. We present results for mothers who were shown fewer than 20 adoptive families (754), 20 potential adoptive families (8,158) and more than 20 potential adoptive families (3,928). Mothers were shown fewer than 20 adoptive families only if no more families fit the race or state criteria given at initial inquiry, i.e., this event is random conditional on the state and race of the mother.[33] Observing only 20 or more than 20 adoptive families is endogenous. The agency sends a second batch of profiles if requested by the mother.[34]

Mothers who see fewer than 20 profiles place their child for adoption 8% of the time, those shown 20 profiles do so 1% and those who see more than 20 profiles do so 13%. Consistent with search theory, search intensity (number of profiles seen) and the probability of placing a child in adoption are positively correlated (0.01 v. 0.13, p-value < 0.0001). Market conditions also appear to affect mothers' behavior, with fewer options resulting in a higher probability of placement (i.e. comparing those who receive fewer than 20 profiles and those who receive at least 20 profiles, 0.08 v. 0.01, p-value < 0.0001). A potential explanation for this latter pattern is that, upon receiving the email with family profiles, mothers update their beliefs

[32] While we know which adoptive family profiles the agency sent birth mothers in emails, we do not know which profiles were inspected or how carefully. We, therefore, have limited data to estimate a search model as in Santos et al. (2012); Caplin et al. (2011).

[33] Using a linear probability model with state fixed effects, we find that a Black mother is 8 percentage points more likely to receive less than 20 profiles and a Hispanic mother is 2 percentage points more likely.

[34] The option value of searching for more adoptive families is higher for mothers who have a higher probability of placing their child for adoption. We follow Hotz and Miller (1993) in using conditional choice probabilities to model the dynamic choice to stop search (see Arcidiacono and Ellickson, 2011, for a review of the approach) and estimate mothers' choices using a conditional logit model (McFadden, 1974). See Table A.1.



(a) Probability of adoption by profiles seen (b) Frequency of adoption by profile order

Figure 2: Menu effects on decisions

Notes: Panel (a) includes all birth mother data. Panel (b) is restricted to birth mothers who saw 20 profiles or less (n=8,208), i.e. they only received the profiles in the welcome email.

about the possibility of finding better alternatives down the road. Being presented a smaller number of adoptive families, i.e., a smaller choice set, would indicate it is less likely to place their child if they wait. Thus, mothers are more likely to place their child for adoption when receiving few profiles.

4.3 Decision attention

Mother decision attention is challenging to measure, especially in our setting. Our data is limited to the recorded characteristics of the birth mother and adoptive family during their interaction with the agency. To construct a proxy for birth mother decision attention, we exploit the quasi-random order of adoptive families shown to birth mothers in the welcome email.

In the email, up to twenty families were shown in alphabetic order by the first adoptive parent's first name (see Figure B.1 for an example of the email). We cannot reject that this order is random (see Tables B.1, B.2, B.3, and B.4 and the analysis in Appendix B). We use this as good as random presentation of families to construct a measure of decision attention.

If a mother chooses the most suitable family from this set and inspects all profiles equally,

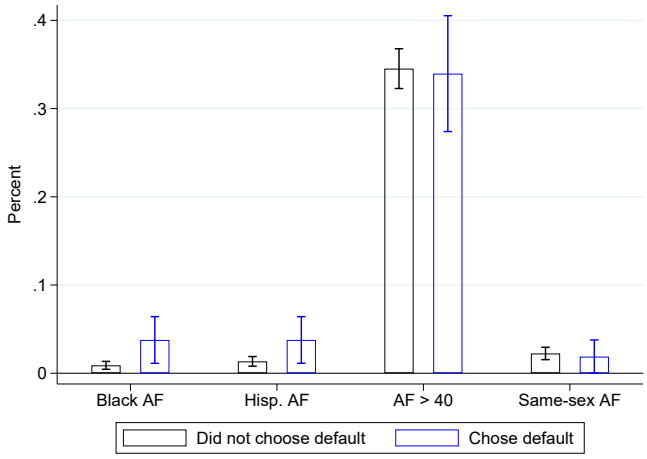


Figure 3: Preferences of adoptive family by choice of default

Notes: "Default" is the first family that appears on the list of adoptive families in the Welcome email. The figure includes only those birth mothers who saw 20 profiles.

we expect the order shown of the chosen family to be uniformly distributed. Figure 2, Panel (b), shows the distribution of the order in which a chosen adoptive family (or an attempted adoption) was shown to a birth mother. We restrict the sample to mothers who were shown up to twenty profiles at most, i.e. those who only received the welcome email, as adoptive families were shown in as good as random order. Profiles with order 1 are overrepresented in adoptions. Indeed, the odds of being selected by the birth mother are 73% lower if a family is in a position other than first on the list (Table A.2) and holds for mothers who arrive early in their pregnancy (12 weeks or more before birth) and those who arrive later (12 weeks or less) (Tables A.3 and A.4).[35] These patterns motivate using the order in the welcome email of the family chosen for placement as a proxy for decision attention, with lower order numbers indicating less attention.

We examine the implications of birth mothers choosing the first family listed in the welcome email on the characteristics of chosen adoptive families. Those who do not chose the "default," i.e. in our setting, the first option, reveal a deliberate decision (see Goldin

[35]Order effects have been shown in other systems. Feenberg et al. (2017) find NBER working papers listed first and last in a weekly email are more likely to be downloaded and cited. Jurajda and Münich (2010) find preference for college admissions for students with earlier alphabetical names in the Czech Republic.

and Reck, 2020). We divide the sample of mothers placing their child for adoption between those who chose the first profile and those who chose from the remainder. Figure 3 compares their choices. Mothers who chose the first option are more likely to select a Black (4%) or Hispanic (4%) family, compared to mothers who did not choose the first option (1%). Given that the distribution of Black and Hispanic families in the pool of adoptive families are 2% and 5% respectively (Table 3), this suggests that mother inattention may mute their preferences when choosing an adoptive family.

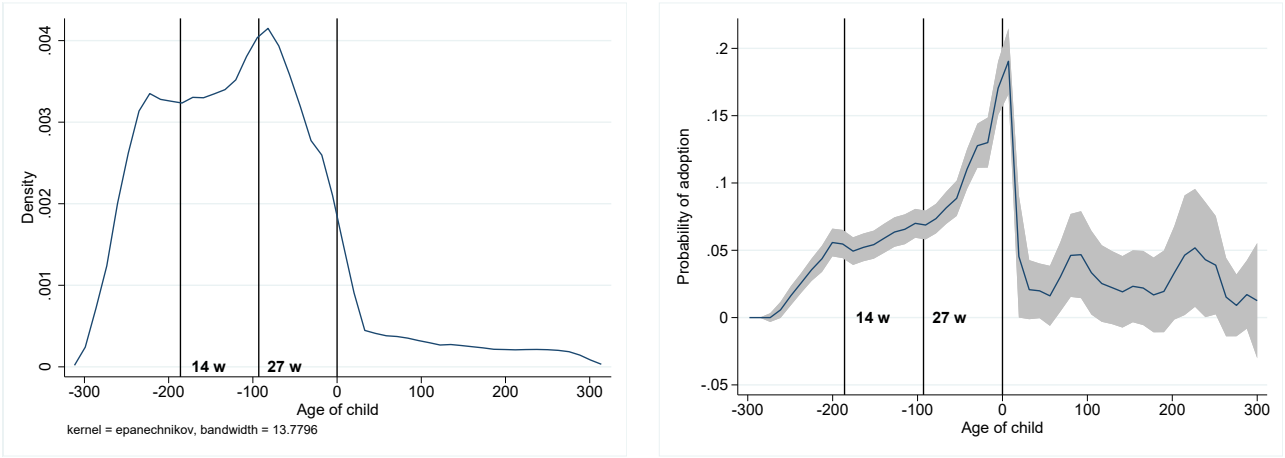
4.4 Costly search with a deadline

Three stylized patterns of behavior suggest mothers engage in costly search with a deadline. These patterns emerge in arrival times, probability of adoption and decision attention.

Figure 4, Panel (a), shows the density function of mother arrivals by the age of the child at first inquiry. Inquiries increase sharply to around week 10 and then are flat until around week 21, after which there is an increase in inquiries that peak around the start of the third trimester of pregnancy (week 27). Arrivals decline sharply after this date and are less frequent once the child is born. The pattern of arrivals is consistent with mothers being aware of limits on abortion during the last trimester and the desirability of the child by age when deciding about adoption.[36] The low frequency of arrivals after birth could reflect a birth mother's belief that adoptive families prefer a newborn or mothers being aware of the difficulty of parting with their child after birth. Our data do not allow us to distinguish between these explanations.

Panel (b) of Figure 4 shows the probability that an adoption is placed by age of the child at first inquiry. The pattern is convex up to the birth of the child, i.e. the probability of adoption reaches 5% around week 12 and increases to almost 20% around the time of birth. The probability plummets to around zero right afterward. In other words, mothers who arrive

[36] Before the U.S. Supreme Court decision in the case Dobbs vs. Women's Health Organization, the right to an abortion prior to fetal viability, i.e. some time around the end of the second trimester of pregnancy (The American College of Obstetricians and Gynecologists, 2017), was protected by the U.S. Supreme Court decisions of Roe v. Wade (1973) and Planned Parenthood v. Casey (1994).



(A) Arrival times

(B) Probability of adoption

(C) Decision Attention

Figure 4: Arrival, adoption and decision attention by age of child (in days) when BM makes initial inquiry

Notes: Distributions are truncated at three hundred days after birth for Panels (a) and (b) and 15 days after birth for Panel (c). Vertical lines indicate approximate trimesters (first: 0-14 weeks; second: 14-27 weeks: third, 27-40 weeks). Panels (b) and (c) show kernel density functions with 95-percent confidence intervals.

late in their pregnancy are significantly more likely to place an adoption than those making initial inquiries earlier. This pattern cannot be explained by mothers who arrive later having already secured an adoptive family and merely needing to complete paperwork. These cases are excluded from our data. Instead, the pattern is consistent with either mothers who arrive late in their pregnancy being different (a distributional change), facing fewer alternatives due to limits on abortion, or being aware of the difficulty of placing or parting with their baby

after birth, and are thus more likely to place their child for adoption.

Panel (c) of Figure 4 shows our measure of decision attention by age of the child at first inquiry. These estimates are conducted in the subsample of mothers who placed an adoption through formal search. We restrict the estimates to 15 days after birth due to the scarcity of data on adoptions for older children. Recall that, because families were presented in as good as random order in the welcome email, a fully attentive mother should disregard order and the average order of the chosen family should be 10. Lower orders suggest less attention. The figure shows that the order the chosen family was presented steadily declines with the age of the child at arrival. We observe a slight increase in decision attention around week 16 and week 28, but the estimates are imprecise. This pattern is consistent with mothers who arrive late in their pregnancy either consider fewer profiles before making a decision or place less weight on the characteristics of the adoptive family, conditional on being acceptable.

5 Abortion restrictions and search

We would like to observe the behavior of mothers when the conditions under which search is taking place change exogenously to determine causal effects. Similar to the search literature on labor markets (Card et al., 2007; DellaVigna et al., 2017, 2022), we focus on changes in outside options.[37]

The U.S. Supreme Court decision in the case Dobbs vs. Women's Health Organization changed a mother's outside options, effectively shortened or eliminated the window over which mothers considering abortion or adoption could search for adoptive families. These mothers would likely need to make a decision earlier.

The Dobbs decision was a policy that varied across states and is thus amenable to a difference-in-difference analysis. To examine the effect of this policy change, we create a variable that equals one if a state had a trigger law and enforced it at the time of the Dobbs

[37]Policy changes in empirical work on unemployment duration tend to be the magnitude and duration of unemployment insurance.

decision and zero if not.[38] We estimate the effect of the policy using regression methods that control for time of arrival after the Dobbs decision (June 24, 2022) and the interaction between living in a trigger state and arriving after the Dobbs decision. These estimates provide intent-to-treat estimates of the policy since not all trigger states implemented the prohibitions immediately. Similarly, non-trigger states also introduced abortion restrictions during this period. We provide several robustness checks of our results.

In the next two sections, we present descriptive evidence of the extensive and intensive margin effects of the Dobbs decision. Subsequently, we present estimates of these effects and heterogeneity analysis. We do not examine the extensive margin policy effects on decision attention or probability of adoption because such analysis uses the subsample who placed a child for adoption (6.8% of mothers). The data are too thin to draw conclusions.[39] Instead, for the extensive margin, we focus on the probability that both the birth mother and adoptive family agree to match. Adoption occurs when the baby is placed with the family after birth.

5.1 Extensive margin: arrivals and adoptions

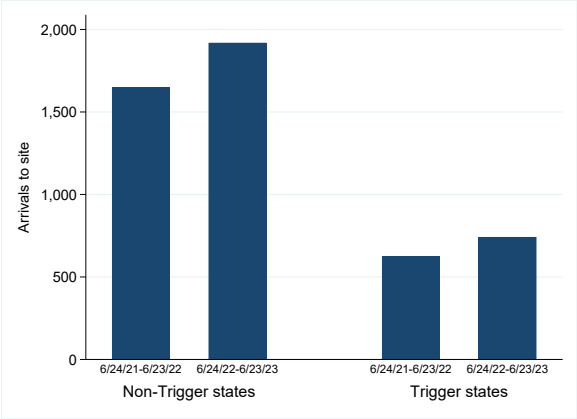
Figure 5 shows changes in arrivals to the agency and matches one year before and one year after the Dobbs decision. The figure on the left shows the total number of unique mothers who make an initial inquiry, and the figure on the right shows the total number of matches. Each figure is further split into Trigger and Non-Trigger states.

Arrivals increase after the Dobbs decision in both Non-Trigger and Trigger states. Matches increase in Trigger states after Dobbs but decline in non-Trigger states. We find no evidence that the composition of birth mothers changed by race or age before or after Dobbs (Table

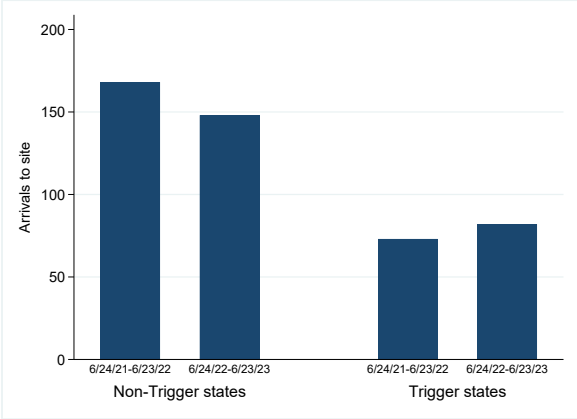
[38] This includes 12 states. According to the Center for Reproductive Rights and Dench et al. (2024), there are 11 states with enforced trigger laws, i.e. that automatically restricted or eliminated access to abortion, at the time of the Dobbs decision: Alabama (AL), Arkansas (AR), Idaho (ID), Kentucky (KY), Louisiana (LA), Mississippi (MS), Missouri (MO), Oklahoma (OK), South Dakota (SD), Tennessee (TN) and Texas (TX). We also include West Virginia (WV) which did not have a trigger law but banned abortions immediately after Dobbs. We do not include Utah and Wyoming. Both states had trigger laws that were immediately contested after Dobbs and then enjoined in July 2022.

[39] Figure A.3 shows the effect of Dobbs on the probability of adoption and Figure A.4 on decision attention. Complier analysis of decision attention is in Appendix B.

A.5). The increase in arrivals and matches in Trigger states after the Dobbs decision suggests a change on the demand side, i.e. more mothers searching for adoptive families.[40] These patterns are noisily estimated for arrivals and matches (Chi-square distribution test p-values of 0.736 and 0.216 respectively).



ARRIVALS (P-VAL = 0.736)



MATCHES (P-VAL = 0.216)

Figure 5: SEARCH AND MATCHES BEFORE AND AFTER TRIGGER ANTI-ABORTION LAWS

Notes: Arrivals are the number of initial inquiries to the agency, and Matches are the number of times a birth mother and adoptive family agree to match. The Before sample includes mothers who made an initial inquiry between June 24, 2021 and June 23, 2022 and After sample includes those who inquired between June 24, 2022 and June 23, 2023. Trigger states are those with trigger laws in place on the date of the Dobbs decision. Non-trigger states did not have laws in place. Reported p-value are for a χ^2 test of equality of distributions.

5.2 Intensive margin: timing of arrival

The timing of birth mother arrivals should reflect environmental conditions. Figure 6 provides descriptive evidence of timing. It compares the child's age at arrival and the child's age at arrival conditional on adoption. The figures on the left are for states without trigger laws, and the figures on the right are for states with trigger laws. Panel (a) presents the cumulative distribution of a child's age at arrival. Each of the two figures in the panel compares the distribution of the child's age at arrival before and after the Dobbs decision. We observe a larger shift in the cumulative distribution in states with trigger laws. In these

[40] Evidence that the Dobbs decision increased births is provided in Dench et al. (2024).

states, mothers make a first inquiry earlier in their pregnancy after Dobbs.[41]

Panel (b) compares the density of the child's age at arrival. Before the Dobbs decision, we observe that the density function spikes just after the start of the third trimester of pregnancy in states with and without trigger laws. This is consistent with mothers considering having an abortion and searching for adoption families as an alternative, especially since late-term abortions are unlikely. After the Dobbs decision, in states with trigger laws, the density shifts earlier in the pregnancy. In states without trigger laws, the density function still peaks at the start of the third trimester. This suggests that abortion restrictions create deadline effects in mothers' search.

Panel (c) compares the cumulative distribution of the age of the child at arrival for children who are placed in adoption in trigger and non-trigger states before and after Dobbs. There is no difference in the distributions in non-trigger states, but we do observe a noisy increase in the age of the child at arrival for those placed in adoption in trigger states.

5.3 Estimates

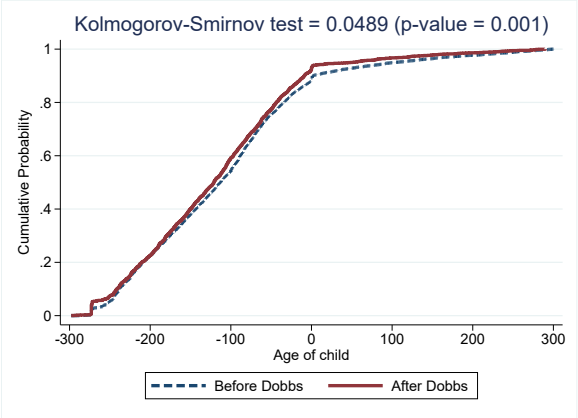
We confirm the timing of arrival effects pre and post Dobbs reported in the previous section with difference-in-difference regression analysis that adds covariates.

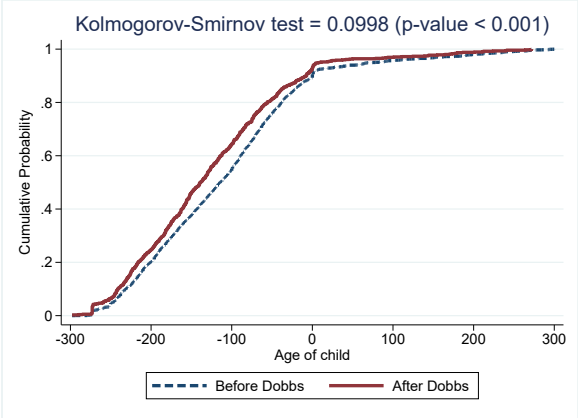
Our main specification is as follows:

$$Y_i = \beta_0 + \beta_1 D_i + \beta_2 T_i + \beta_3 D_i T_i + \beta_4 X_i + \epsilon_i \tag{1}$$

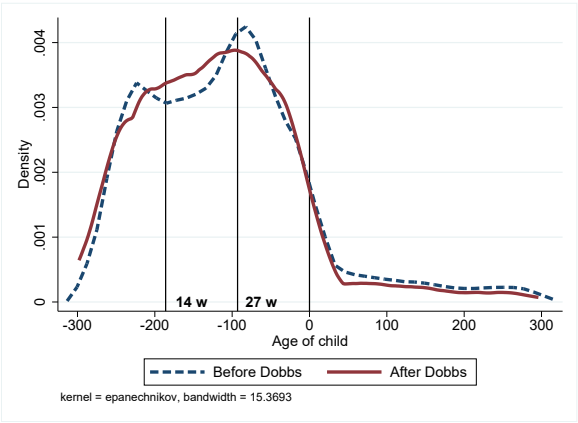
where Y_i is the age of the child at mother's arrival. D_i is a dummy variable for arrival on June 24, 2022 or thereafter, T_i is a dummy variable for the mother living in a trigger state, $D_i T_i$ is an interaction term, X_i is a set of controls for i, including mother's age and whether she is White or Black. We run quantile regressions to account for changes in the distribution of arrival times.

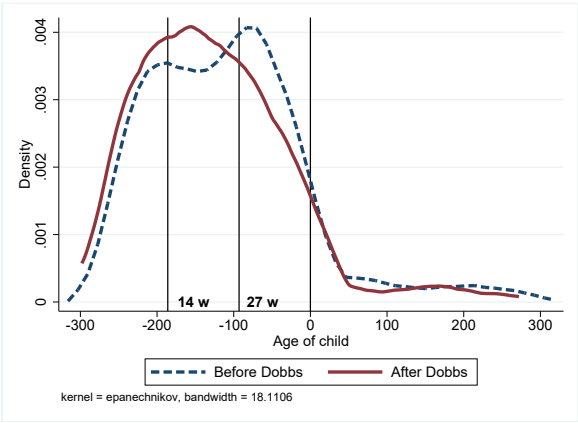
[41] The shift in the distribution of arrival times in trigger states after the Dobbs is significant and confirmed by first-order stochastic dominance tests (Table A.6).



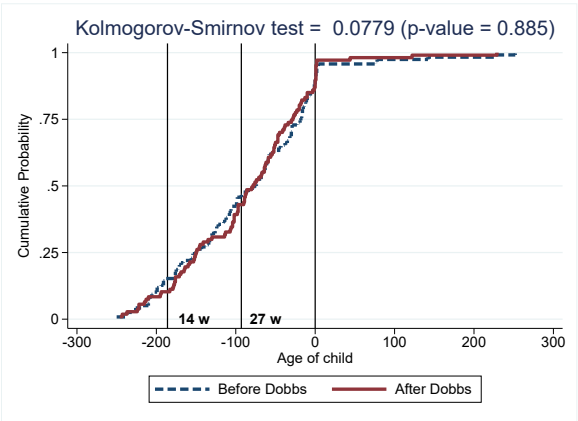


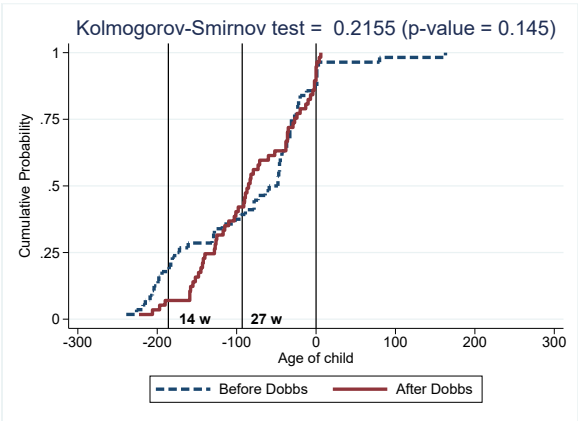
(A) Cumulative distribution of age of child at arrival





(B) Density function of age of child at arrival





(C) Cumulative distribution of age of child if adopted

Non-trigger states Trigger states

Figure 6: Search and adoptions before and after trigger anti-abortion laws

Notes: Trigger states are those with trigger laws in place on the date of the Dobbs decision. Non-trigger states did not have laws in place. Panel (b) densities are estimated using Stata's kdensity. Panel (c) uses a restricted sample of initial inquiries from June 24, 2021 - June 23, 2022 or June 24, 2022 - June 23, 2023.

We confirm there are no pre-existing trends in arrival times in trigger and nontrigger states prior to Dobbs but diverge post-Dobbs (Figure A.2), lending support for our difference-in-difference identification. Figure 7 plots the coefficient on the interaction term, β_3, from Equation 1 by quantile.[42] The effect of Dobbs in trigger states is to significantly lower the age of the child at arrival along most quantiles of the distribution. The median age of the child at arrival is 15.2 days younger. This confirm the finding from Figure 6, Panel (a). This effect is a 13.7 percent decrease with respect to the average age of the child at arrival (-110.8, s.d. 105.7).[43]

We conduct several robustness checks of our results. First, to account for potential pre-existing trends, we run a placebo check and estimate the model assuming that the Dobbs decision occurred a year earlier. We exclude from the regressions observation after Dobbs. We do not find a significant effect of the Dobbs decision in trigger states in these regressions (Table A.10).[44] Second, we estimate the overall impact of the Dobbs decision on search timing by implementing a changes-in-changes regression (Athey and Imbens, 2006). While less precisely estimated, we confirm that the Dobbs decision induced initial inquiries earlier in a mother's pregnancy (Table A.12). We also estimate these regressions in the subsample used in Dench et al. (2024). The authors restrict the sample to make those not affected by Dobbs more comparable to those affected by it. Our results are similar in this sample (Table A.8). We are not well-powered to implement Arkhangelsky et al. (2021)'s synthetic difference-in-difference approach as in Dench et al. (2024) because we only have a balanced panel at the highest level of aggregation in the data (i.e. state by semester).

In sum, we find robust evidence that the Dobbs decision increased mothers' search intensity, i.e. there was a 13.7 percent decline in age of the child at birth mother's initial

[42] Table A.7 reports the quantile regressions results used for Figure 7.

[43] Similar results hold in an unrestricted sample. Using results from Table A.9, this is $-\frac{10.96}{110.8} = -9.9$.

[44] To further investigate the robustness of this placebo regression, we add a dummy variable for Texas and an interaction term for Texas and post-Dobb period. We do this because Texas accounts for 35% of the cases in trigger states in our data and because Texas has implemented several restriction to abortion prior to the Dobbs decision. Table A.11 report these estimates. We find no significant changes in our results using this specification.

inquiry.

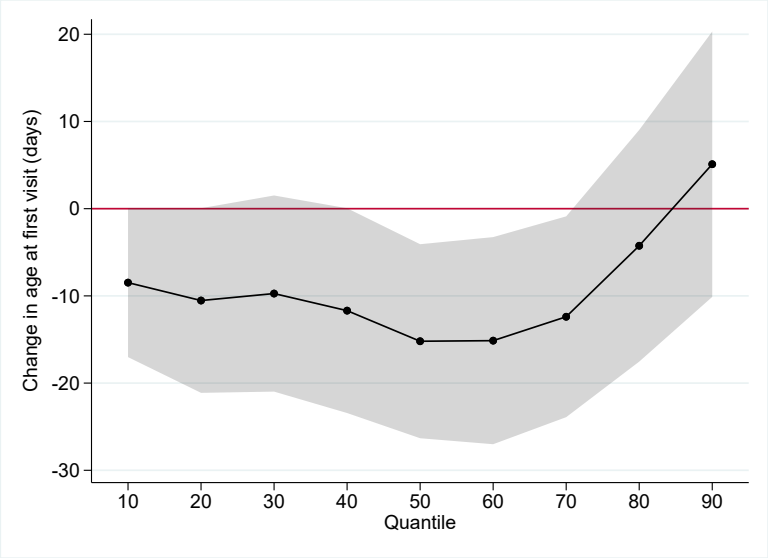


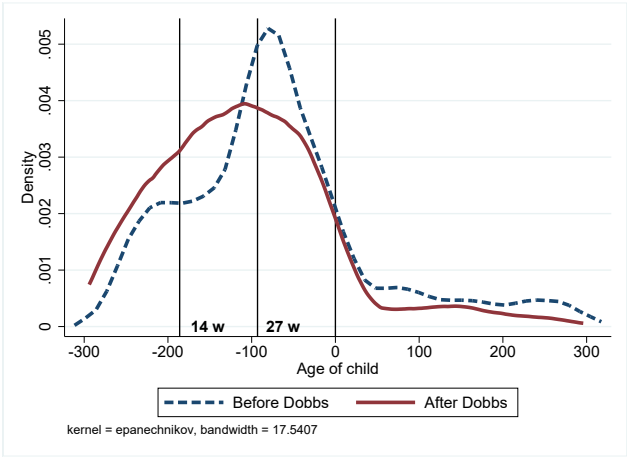
Figure 7: Effect of Dobbs on search (quantile regressions)

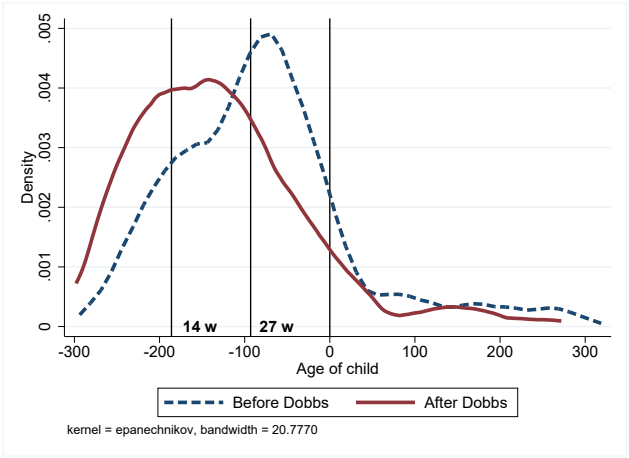
Notes: The shaded portion of the figure indicates 90-percent confidence intervals.

5.4 Heterogeneity

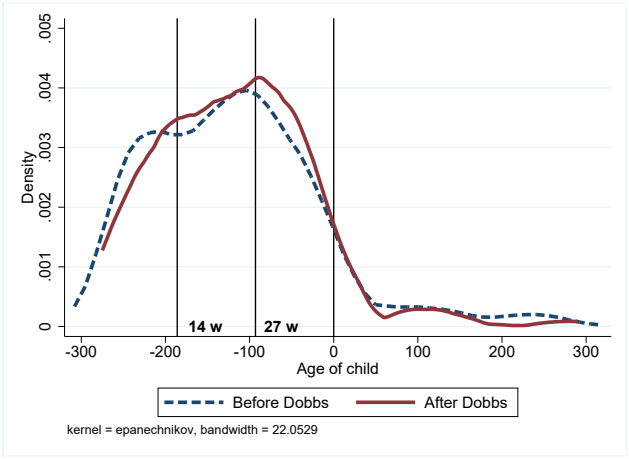
Black, Hispanic and White mothers in our sample do not make initial inquiries at the same time during pregnancy (see Table 1). We explore if policy changes affected these populations differently on the intensive margin. Heterogeneity on the extensive margin is examined in Section 6.2.

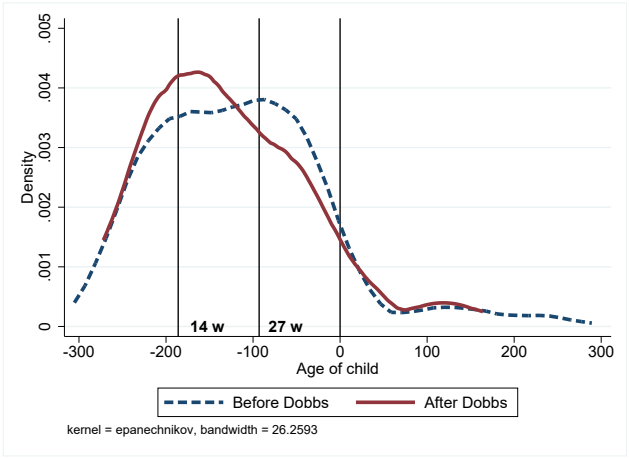
Figure 8 shows changes in the distribution of arrival times by race before and after the Dobbs decision in states without and with trigger laws. Black mothers react most strongly to changes in abortion laws, with Hispanic mothers reacting but to a lesser degree. Indeed, the distribution of arrival times for Non-White mothers resembles that of White mothers after the Dobbs decision. These results are confirmed with estimates of Equation 1 separately for Black, Hispanic and White mothers (Tables A.13, A.14 and A.15). The median age of the child at arrival decreased by 25.5 (s.d. 8.2) days for Black mothers, 26.9 (s.d. 17.1) days for Hispanic mothers and 8.2 (s.d. 9.8) days for White mothers.



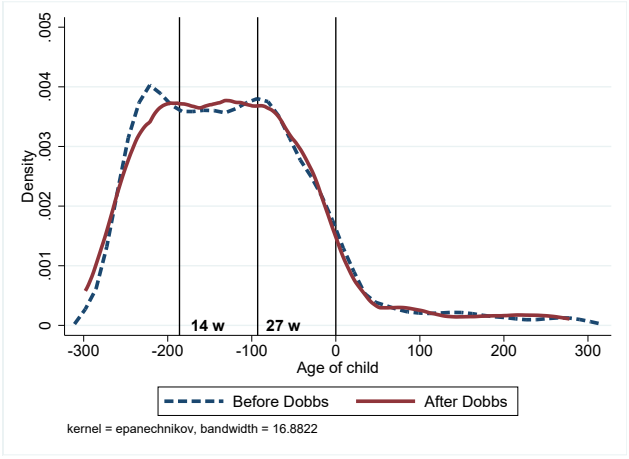


(A) Black mothers

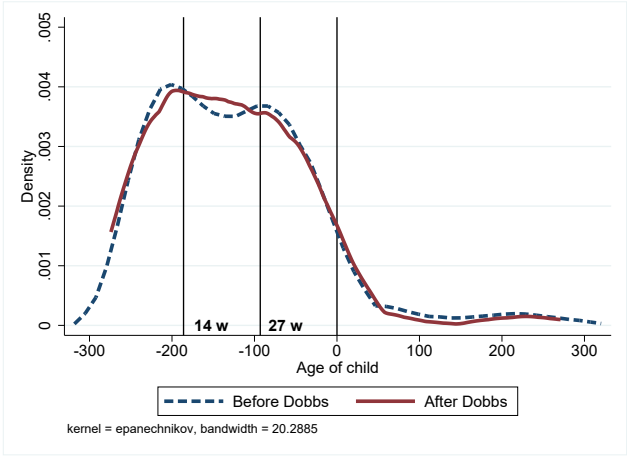




(B) Hispanic mothers



States without trigger laws



States with trigger laws

(C) White mothers

Figure 8: Density function of age of child at arrival pre and post Dobbs

Notes: Densities are estimated using Stata's kdensity.

These heterogeneous effects can be explained partially by the differential timing of arrival across groups pre-Dobbs. White mothers are more likely to make an initial inquiry before their second trimester, Black mothers around the start of the third trimester, and Hispanic mothers in between (Figure A.1). These patterns mean that Non-White mothers are more likely to be affected by abortion restrictions. They are also consistent with Non-White mothers facing larger constraints as they search for an adoptive family. For example, in our sample, adoptive families have a stronger preference for a White or Hispanic child over a Black child (see Table 3).[45] This was also documented by Landes and Posner (1978); Baccara et al. (2014). More importantly, this suggests that welfare losses are likely concentrated in minority populations.

6 Birth mother decision framework

The stylized patterns reported in Section 4 are consistent with a search model with deadlines. Deadline effects are visible at the child's birth, where arrivals to the agency decline sharply, and around the second and third trimester of gestation, where limits to have an abortion are present. The sharp increase in the probability of adoption and the decline in decision attention at the child's birth are also consistent with deadline effects.[46]

Our information on mothers' search efforts is limited. We have detailed information on a mother's interactions with our partner, however, we do not observe search outside of those interactions. We interpret an inquiry to the agency as an indication that the mother has actively considered placing the child for adoption. We keep these issues in mind as we model mothers' behavior and derive testable implications.

[45] This is consistent with our sample of adoptive families being overwhelmingly White (92%) and having a preference for same-race children.

[46] To further understand what might be driving a birth mother's decision, we conduct a qualitative analysis using conversations scraped from an online discussion board focused on adoption (see Appendices C and D). We categorize posts by birth mothers using a large language model (LLM). Timing of adoption and order of viewing family profiles during search emerge as important reasons for choosing a family. This provides additional support for our modeling choices.

6.1 Search model

The adoption setting we examine is one where birth mothers choose from a set of potential families who find the birth mother acceptable. We conceptualize this situation as a one-sided market in which mothers engage in costly search for an adoptive family.

The model addresses two features of the search process: (1) how intensely to search for an adoptive family and (2) whether to choose an adoptive family from those available. We assume the search occurs over discrete periods like weeks, months, or trimesters. Given its significance, we consider the birth period to be 0, and k represents periods after birth. A negative k denotes periods before birth. For simplicity,[47] we assume that birth mothers can search for an adoptive family up to one period, i.e. $k = -1$, before birth and have to exercise their outside option once the child is born ($k \geq 0$). R_k represents the outside option to placing the child for adoption. The outside option includes the possibility of having an abortion, which is associated with lifetime utility A, and the possibility of raising the child, which is associated with lifetime utility H. We let R_k depend on the period k since the option set changes as the option of abortion disappears over time.

In a period in which a mother can place a child for adoption, she decides how intensely to search for an adoptive family. The intensity of the search in period k is denoted as s_k, where $s_k \in [0, 1]$. The intensity of the search, s_k, determines the probability of finding a conditionally acceptable adoptive family.[48] This family is the best among those inspected, and the mother attributes a lifetime utility equal to u_k. In our setting, accepting a family for adoption carries a monetary transfer M_k that depends on the baby's age. These transfers are typically used to cover the costs incurred during pregnancy. We do not model this variable explicitly, i.e., we assume $\forall k, M_k = 0$, because we do not have complete information on transfers and it does not significantly alter the hypotheses of the model we want to test.

The distribution of the best option is $F_k = F$, which we assume is stationary over the

[47] See Appendix E for a model of search that relaxes these assumptions.

[48] We normalize search intensity to represent the probability that at least one adoptive family is found. See Le Barbanchon et al. (2024) for a discussion of this model in the labor literature.

relevant time in which the mother makes her decision.[49] We observe the characteristics of the adoptive families on our partner's website, but we do not observe the alternatives the mothers sees. A mother incurs cost $-c(s_k)$ if she wants to find a family with probability s_k. We assume that the cost function is increasing, strictly convex, and equals 0 if search is not pursued. If the observed utility is u_k, the mother chooses the family or waits until the next period to decide. We denote the expected utility, conditional on being able to search, of waiting until the next period by v_{k+1}. If the search produces no adoptive family (which occurs with probability $(1 - s_k)$), the mother waits. We assume that search intensity does not affect the distribution of alternatives.[50] We denote $R_k = max\{A, H\}$ if A is available and $R_k = H$ if not. We let R denote the vector of values of R_k affecting mothers' decisions. We note that in our model, mothers search for adoptive families for as long as possible if no suitable family is found. Mothers exercise the outside option, i.e. abortion or raising the child themselves, only when no more search is possible. We consider this a reasonable assumption given the revealed interest in the possibility of adoption of the mothers in our study.

Search intensity s_k can be interpreted as a rescaling of arrival times within a period if the probability of finding an adoptive family monotonically increases in earlier arrival time and the cost function is the cost associated with arrival time. Our current presentation simplifies the algebra significantly and helps relate our approach to previous literature on job search (Card et al., 2007; Chetty, 2009).

The expected utility conditional on being able to search in period $k, (k < 0)$ is as follows:

$$v_k(R) = -c(s_k) + s_k E[\max\{u_k, v_{k+1}(R)\}] + (1 - s_k)v_{k+1}(R) \tag{2}$$

and $v_k(R) = R_k, k \geq 0$.

[49] Over 300 adoptive families are added to the site each year, roughly equivalent to the number of adoptions placed each year. Around 3,000 different mothers visit the agency's website each year.

[50] This assumption simplifies the analysis since allowing the distribution of the best option to depend on the intensity of the search would complicate the algebra without adding much economic insight.

The dependency of v_k on k is handled using subscripts, and we avoid cluttering the notation by not using subscripts for R_k. Expected utility is a function of search cost c_k in period k and the weighted average of flow utility when search is successful and unsuccessful. We can rewrite the original problem as:

$$v_k(R) = -c(s_k) + s_k \int_{v_{k+1}(R)}^{\infty} (u_k - v_{k+1}(R))dF(u) + v_{k+1}(R) \tag{3}$$

$$= -c(s_k) + s_k Q(v_{k+1}(R)) + v_{k+1}(R), \tag{4}$$

where $Q(v_{k+1}(R))$ is the *average* gain from an adoption on searching at time k. Note that $\partial Q(x)/\partial x \leq 0$, i.e. as the outside option, R, gets better the gain for searching for adoptive parents declines (i.e., people are more likely to put off searching).[51] The continuation valuation of search declines with K, i.e. as the deadline approaches.[52] This implies that the probability of adoption, i.e., the willingness to accept worse matches, increases as the deadline approaches. Note that the outside option, R_k, weakly worsens if the option of an abortion is no longer available. This means that search intensity should increase in anticipation of such an option being removed, and the probability of adoption conditional on search should also increase if such an option is removed.

The dependence of $v_k(R_k)$ on the outside option speaks to selection issues in the adoption market. Mothers with relatively lower R's should enter the market earlier, search more intensely, and be more likely to place the child for adoption to a given family. Strong enough selection effects can produce results contrary to a finite horizon search model. It is an empirical question whether deadline or selection effects dominate this market.

The model captures what we uncover with our data through the following predictions.

Prediction 1: Search intensity should increase in anticipation of an outside option being

[51] Nonetheless, the value function is increasing in the outside option since agents choose their best option.

[52] To see this, note that a mother can attain v_{k+1} by setting $s_k = 0$ and chooses $s_k > 0$ only if this increases ex-ante expected gains.

removed.

Prediction 2: Search intensity will increase as birth of the child approaches.

Prediction 3: As the deadline approaches, the reservation utility decreases so the willingness to accept worse matches increases, i.e. decision attention, declines.

6.2 Model evaluation

Before moving to welfare analysis, we examine whether initial matches and search are positively correlated, as predicted by theory. All the analysis restricts our sample to one year before and after the Dobbs decision. We consider matches, instead of final adoptions, because they are a revealed preference measure of the desire of a birth mother to give a child in adoption to a particular family. While roughly 34% of matches do not lead to an adoption, they provide a more expansive measure of the willingness to match.

Figure 9 evaluates the model using cross-sectional data and behavioral changes due to Dobbs. The left panel plots average days to birth upon arrival to the agency and probability of matching for White, Hispanic, and Black mothers. We see that White mothers arrive the earliest and are the most likely to match. Black mothers arrive the latest and are the least likely to match. Hispanic mothers look similar to White mothers. This is consistent with the model if we allow for pre-existing differences in the probability of completing an adoption across populations. The pattern of matching is similar if we consider adoptions among shown profiles (see Table 1) or we consider finalized adoptions.

The right panel of Figure 9 exploits policy variation to further test the main prediction of the model. We use a difference-in-difference model to estimate the effect of Dobbs in trigger states on days to birth and the probability of matching, and the estimated parameters are the effect of being in a trigger state after Dobbs. We see that Black mothers arrive earlier and increase the probability of matching. Dobbs has an effect on the distribution of arrival times (Figure A.5), with effects for Black mothers being significant at lower quantiles. This analysis shows that arrival times are a likely valid measure of search intensity.

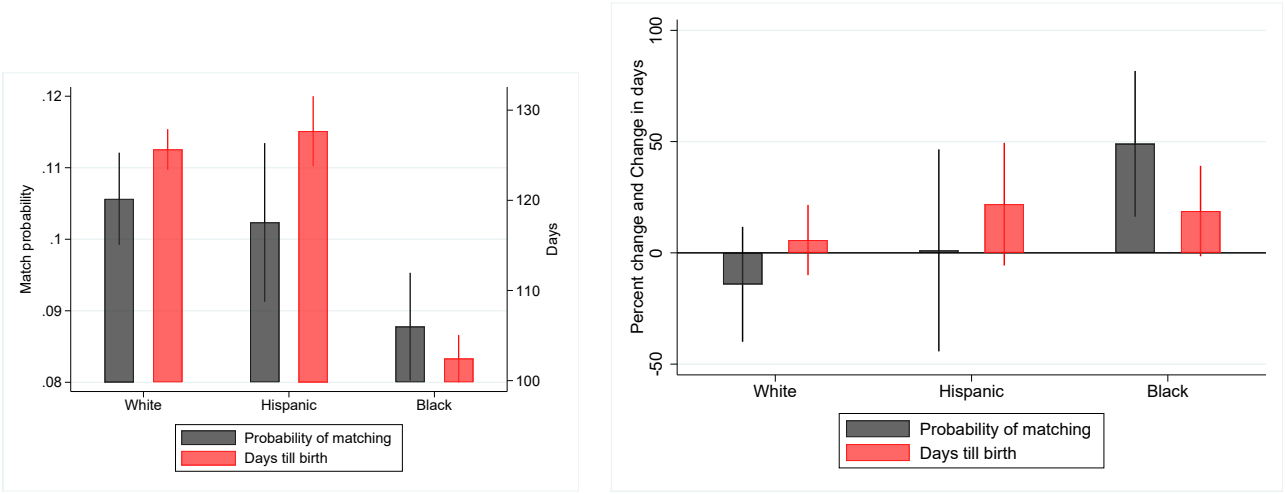


Figure 9: Search intensity and probability of matching

Notes: The figures use a restricted sample of initial inquiries from June 24, 2021 - June 23, 2022 or June 24, 2022 - June 23, 2023. The left panel shows the average days until birth at initial inquiry and the probability of matching with an adoptive family. The right panel shows the estimated parameters of a difference-in-difference model of the effect of the Dobbs decision in trigger states. Bars are 90-percent confidence intervals.

6.3 Evaluating welfare effects

To derive welfare implications of policy changes, we use equation (4). Consider legislation preventing mothers from having an abortion in the second trimester of pregnancy. These restrictions can be modeled as changes in R_k. Using the envelope theorem, the welfare effect of changing option R_{k+1} is:

$$\frac{\partial v_k}{\partial R_{k+1}} = (1 - P(A_k)) \frac{\partial v_{k+1}}{\partial R_{k+1}} \geq 0 \tag{5}$$

where $\frac{\partial v_{k+1}}{\partial R_{k+1}}$ accounts for the possibility that a change in R affects future value functions.

To illustrate the welfare effects, consider no adoptions are possible in period $k+1$. In that case, equation (5) collapses to $(1 - P(A_k))$ since $\frac{\partial v_{k+1}}{\partial R_{k+1}} = 1$. This is equivalent to Roy's identity which shows that the welfare effect of a price change is proportional to the demand of the good.[53] Now consider the decision in period k-1 and assume for simplicity

[53]The equivalence holds due to our assumption that search costs are separable, i.e., the marginal utility of money is one.

that period $k-1$ is the previous to the last period in which adoption is possible. It follows that $\frac{\partial v_{k+1}}{\partial R_{k+1}} = (1-P(A_{k-1})) \times (1-P(A_k))$. In this model, the welfare effect of future changes in outside options decreases with the probability of finding a suitable adoptive family, which in turn, increases with periods of search. Thus, a birth mother can reduce the chance of changes in future outside options affecting search by searching for adoptive families earlier.

Some of the parameters in equations (5) can be estimated from the data, i.e. $1-P(A_k)$. However, the remaining parameters are not directly observable. Thus, we follow previous research (e.g. Chetty, 2009; Card et al., 2007) to derive welfare comparisons from observed behavioral changes by examining changes in search (s_k) due to policy changes.

By total differentiation of the first-order condition of (4), $-c'(s_k) + Q(v_{k+1}(R)) = 0$, we obtain:

$$\frac{\partial s_k}{\partial R_{k+1}} = \frac{P(A_k)\frac{\partial v_{k+1}}{\partial R_{k+1}}}{-c''(s_k)} \tag{6}$$

The equation shows that changes in welfare are proportional to changes in search behavior. In other words, suppose there are two policies affecting birth mothers' outside options, R and R'. If these changes are small enough, we have that $\frac{\frac{\partial s_k}{\partial R_{k+1}} dR}{\frac{\partial s_k}{\partial R_{k+1}} dR'} \approx \frac{\frac{\partial v_k}{\partial R_{k+1}} dR}{\frac{\partial v_k}{\partial R_{k+1}} dR'}$ since they are both proportional to dR, dR'. These calculations require verifying that average behavior is comparable across policies. This close connection between welfare and behavior is due to the assumption of separability of search costs.

6.4 Empirical welfare implications for mothers

Equations (5) and (6) show that we can obtain relative welfare measures by calculating the ratio of the effect of alternative policies on search behavior. We use this approach to assess the welfare effect of the U.S. Supreme Court decision in the case Dobbs vs. Women's Health Organization. The alternative policy we evaluate is the three distributions of stimulus checks in 2020-2021 after the COVID-19 pandemic. Because transfers may have affected

arrival times, this policy is a useful comparison. It can provide a money equivalent of the welfare effect of Dobbs on women who have revealed they consider adoption an alternative.

Only households with relatively lower income qualified for all these transfers, so the analysis is restricted to mothers living in zip codes with median income below $75,000 (see Appendix F for the detailed analysis). We further restrict the sample to Black mothers as they are the most responsive to the Dobbs decision. Because our data do not include information on a birth mother's family structure, we take a conservative approach and evaluate the effect of a one-time transfer of $1,166.7. This is the average amount received across the three stimulus checks for a single person. We find that this transfer increased the child's age at arrival by around 20 days at the mean. For the same population, Dobbs decreased the child's age at arrival by 25 days at the median (18.9 at the mean). These changes are in excess of 25 percentage points since the median (average) child's age at arrival for this group in the year before Dobbs is -84 days (-76 days).

We would like to compare changes in behavior due to the stimulus checks and Dobbs to assess relative welfare effects. One concern is that arrival time changed the probability of adoption before and after Dobbs so welfare would be confounded with a change in search success. Figure A.3 shows this is not the case. The probability of adoption by arrival time is similar before and after Dobbs in trigger states. Thus, we cautiously conclude that Dobbs is equivalent to a loss of at least $1,166.7 in income for the women in our sample. This is consistent with recent research on the causal impact of denied abortion in Colombia (Londoño-Vélez and Saravia, 2025) that shows a negative impact on the health of the mother and her long-term outcomes. We note that, because our sample is mothers who reveal they consider adoption as an alternative, our welfare measure reflects the impact on that subpopulation. Our welfare measure would be a lower bound if we consider that other populations who would not carry a child to term for an adoption in the absence of the abortion restrictions face additional welfare costs not captured in our sample.

The simple search model and our analysis demonstrate that birth mothers engage in

compensatory behaviors. Outcomes, i.e. births, abortions and adoptions, are the result of these behaviors and market constraints. We cannot examine all these outcomes with our data because we do not know the child's outcome for mothers who do not complete an adoption with our partner. Thus, we appeal to supplemental information. Dench et al. (2024) report a 2.3 percentage point increase in births in states where abortion bans took hold after the Dobbs decision. Also, according to the CDC, there was a 36,270 decline in abortions in trigger states in 2022 in comparison to 2021. In non-trigger states, there was an 18,256 increase in abortions.[54] These patterns are consistent with a birth mother exercising her outside option after a policy change.

In sum, our analysis shows an unambiguous decline in welfare after the Dobbs decision, roughly equivalent to a $1,166 decrease in income (2.9% for someone with income of $40,331, the median of the median income for Black non-family households across the zip codes in our data[55]). Our data cannot determine if the quality of matches between children and adoptive families deteriorated. What we can conclude is that mothers' perceived welfare loss due to restrictions on abortion is significant.

7 Conclusion

We investigate the search behavior of birth mothers looking for adoptive families using administrative data from a large licensed adoption agency platform in the U.S. We report several stylized facts. First, women make an initial inquiry roughly three and a half months prior to their due date, with Black mothers arriving closer to their due date than White and Hispanic mothers. Second, mothers' search and the probability of adoption increase with deadlines. Third, we find evidence of default effects. Mothers do not seem to fully explore the set of options presented to them. These effects are stronger as the child's birth approaches. We also establish that policy changes affect mothers' decisions. A reduction in

[54] These numbers correspond to the residence of the mother, not where the abortion took place.

[55] Median income was calculated using the American Community Survey data (file ACSST5Y2023.S1901-Data) which has 5-year estimates of household income (based on pooled data from 2019–2023).

decision horizons, due to a restriction on abortions, leads to an increase in search. These facts support characterizing mothers' behavior with a search model with deadlines.

This characterization enables us to produce revealed preference measures of perceived welfare losses due to the U.S. Supreme Court decision in the case Dobbs vs. Women's Health Organization that limited reproductive health rights. After Dobbs, in trigger states that implemented abortion restrictions immediately, we observe an increase in adoptions, and mothers arriving earlier in their pregnancy. This policy change had the strongest impact on Black mothers, who make initial inquiries far earlier in their pregnancies post Dobbs. We estimate these new constraints on abortion access are equivalent to a $1,166 loss in income (1.6% decrease of median income in our data, and 2.9% decrease for Black birth mothers).

Establishing that mothers behave as in standard search models with deadlines, as used in the labor literature on unemployment insurance, is a first step in characterizing the dynamic aspect of matching in this context. Establishing also that mothers' willingness to place an adoption increases with the deadline suggests that there might be ways to improve the adoption process and the decision-making of mothers. Previous research has shown that the existence of heterogeneous deadlines can affect market structure (see Coey et al., 2020). The reason for the co-existence of adoption platforms and decentralized adoptions might be that mothers' options decrease with time. The adoption market is a two-sided market without money. Conditional on adoptive families' preference restrictions, the platform implements a random dictator assignment mechanism where order is determined by arrival time. Determining the optimal design of adoption platforms requires characterizing both sides' outside options and strategic behavior. We leave that task for future research.

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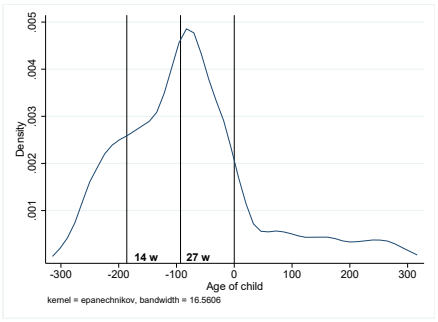
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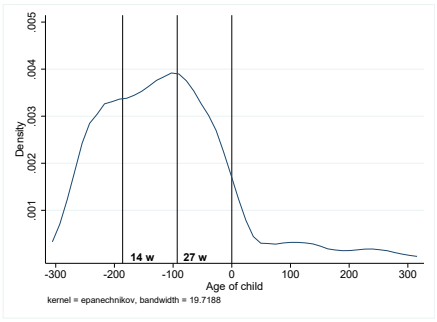
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APPENDICES INTENDED FOR ONLINE PUBLICATION

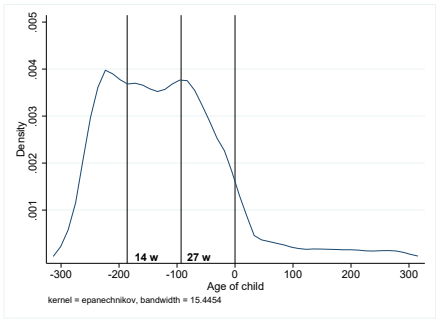
A Additional figures and tables



Black mothers

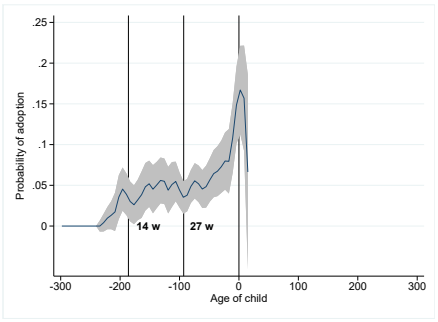


Hispanic mothers

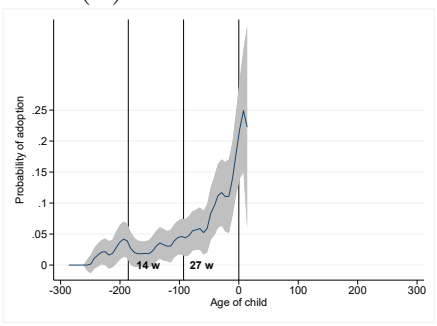


White mothers

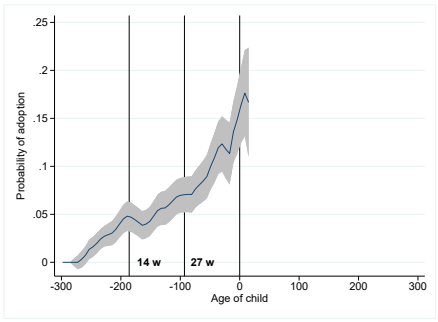
(a) Arrival times



Black mothers

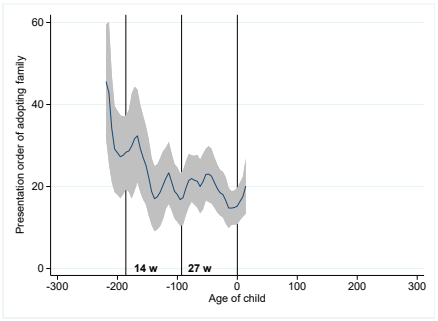


Hispanic mothers

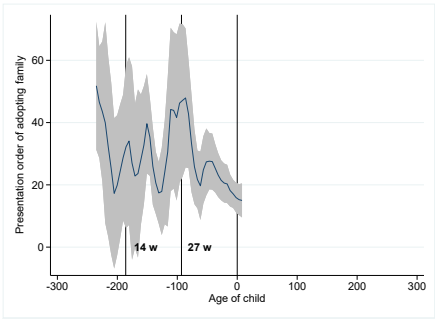


White mothers

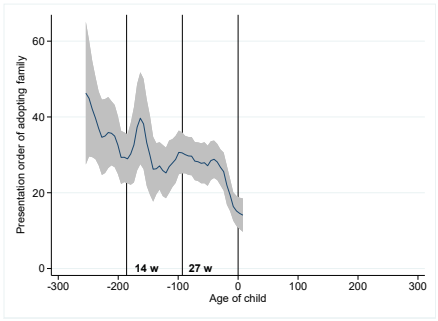
(b)Probability of adoption



Black mothers



Hispanic mothers

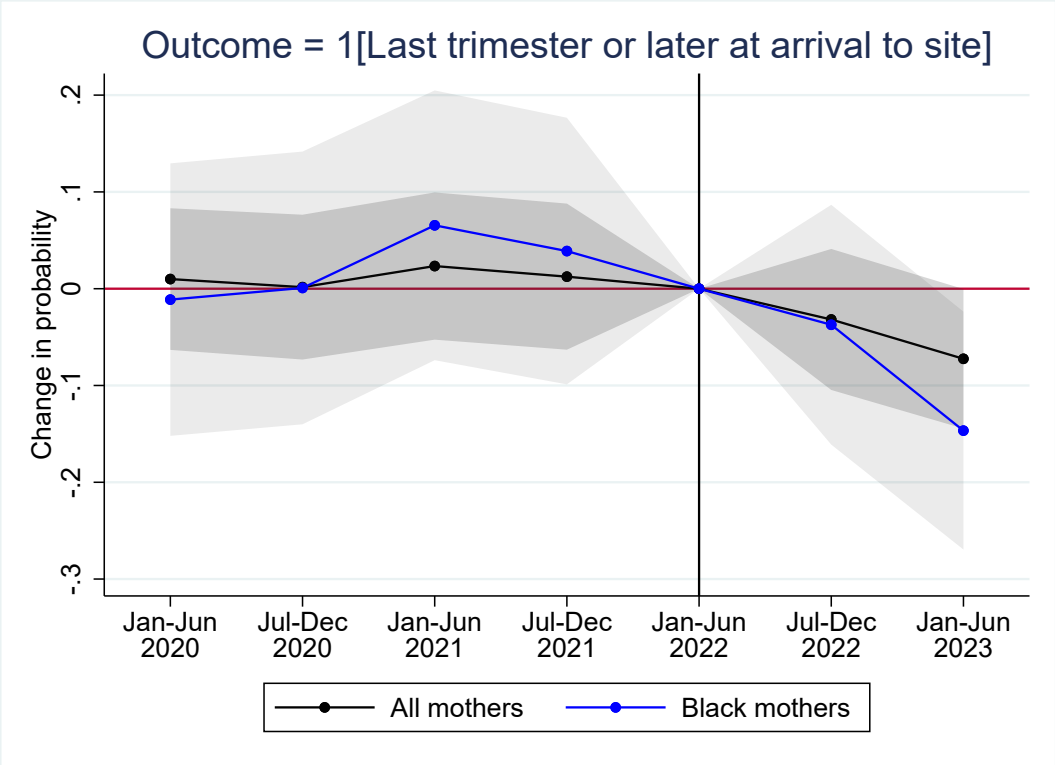


White mothers

(c) decision attention

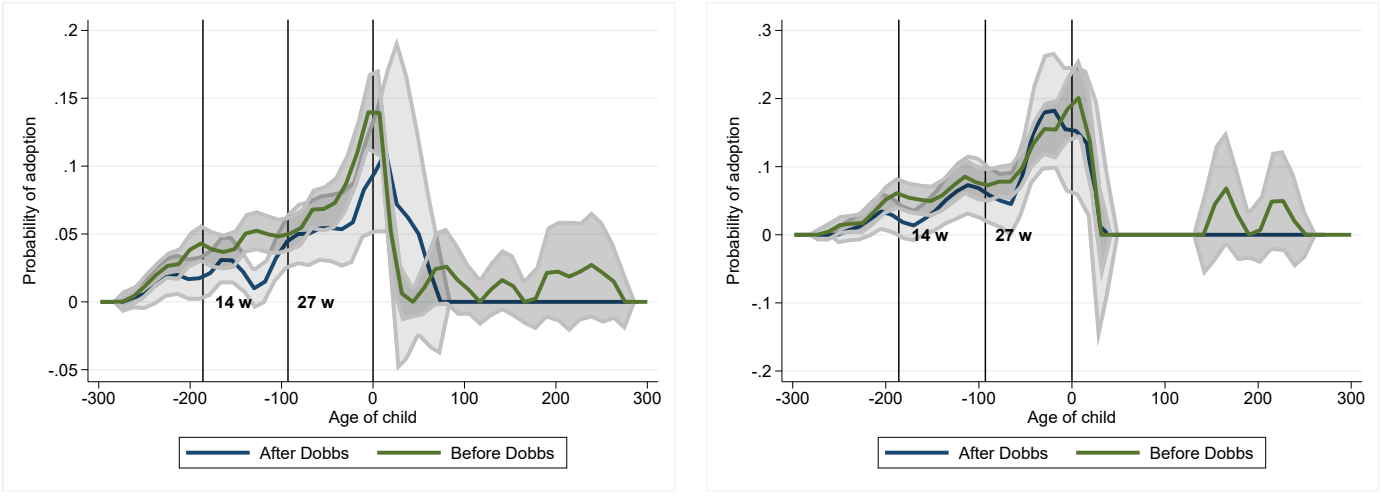
Notes: Distribution truncated at three hundred days after birth.

Figure A.1: Arrival, adoption and decision attention by age of child (in days) when birth mother makes initial inquiry by race of mother



Notes: The dependent variable equals one if the baby's age at arrival is one trimester or older. The regression controls for semester×year, whether the state is a trigger states, dummies for birth mother's race, and birth mother's age. The parameters report the difference in the probability a baby is in the third trimester or older in trigger states for semester before and after Dobbs. These effects are relative to the difference in this variable between trigger and non-trigger states between January and June of 2022. 90 percent confidence intervals are in gray. The estimation uses data from January 2020 to June 2024.

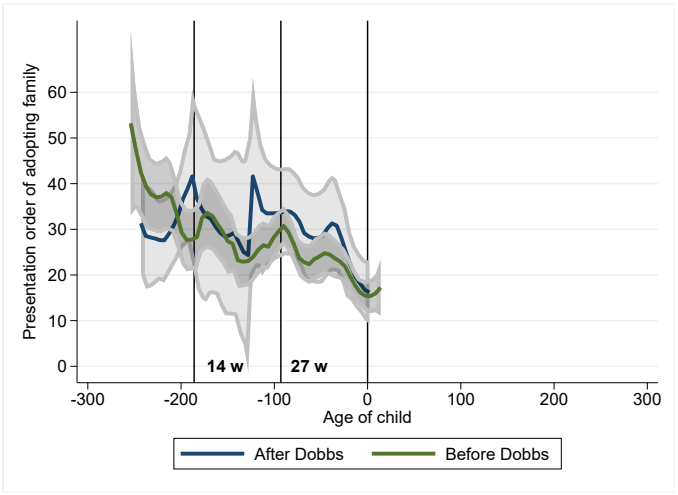
Figure A.2: Parallel trends - Effect of Dobbs in trigger states



Non-Trigger States

Trigger States

Figure A.3: Effect of Dobbs on the Probability of Adoption

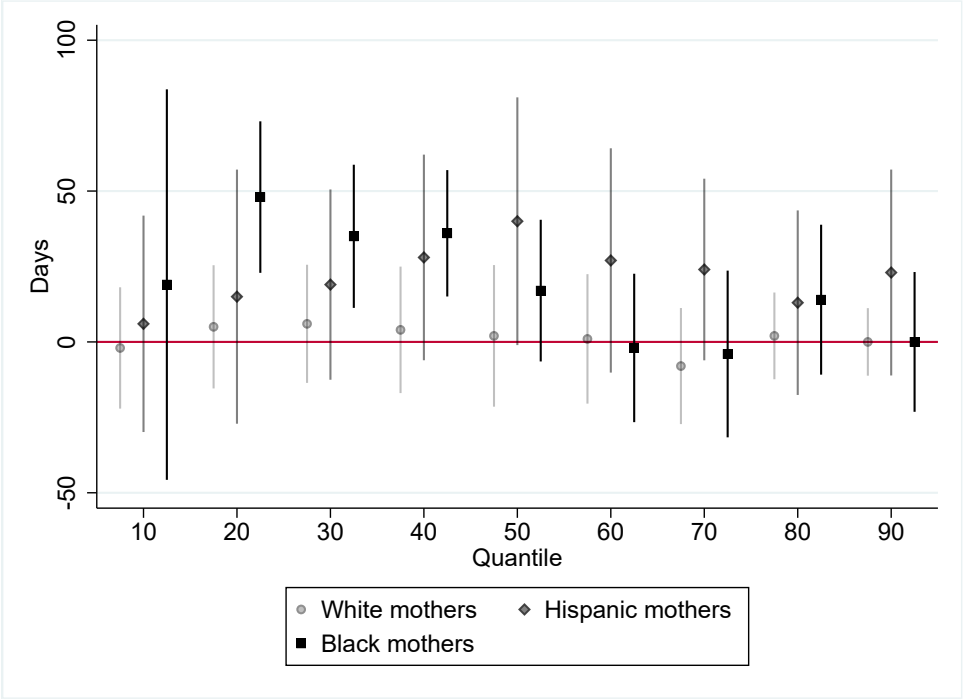


Non-Trigger States



Trigger States

Figure A.4: Effect of Dobbs on Decision Attention



Notes: The figure uses a restricted sample to harmonize comparisons. The Before sample includes mothers who made an initial inquiry between June 24, 2021 and June 23, 2022 and After sample includes those who inquired between June 24, 2022 and June 24, 2023.

Figure A.5: Distribution changes in arrival times due to Dobbs

Table A.1: Option value of having additional menus to search

	All	Excluding repeats
AGE	0.018	0.018
	(0.001)	(0.001)
Black (AP1)	-1.709	-1.688
	(0.581)	(0.581)
Hispanic (AP1)	1.045	1.050
	(0.056)	(0.056)
College ed. (AP 1)	0.098	0.103
	(0.079)	(0.079)
Mixed-race couple	-3.858	-3.778
	(0.155)	(0.150)
Same-sex couple	-3.365	-3.370
	(0.191)	(0.194)
Prob. adoption in new batches	4.493	5.783
	(0.335)	(0.394)
Mothers	11643	11588
Profiles	256106	254936

Notes: Conditional choice model (Logit). Dependent variable is estimated probability of placing the child for adoption. Standard errors in parentheses. AF is adoptive family. AP1 is the first parent in the adoptive family. Prob. adoption in new batches is the probability of requesting a new batch of profiles (-ln(1-Prob. adoption)). Using Small and Rosen (1981) log-sum formula (the denominator of the conditional logit formulas), we calculate the expected welfare of each choice set and estimate the percent loss of eliminating the option to ask for more profiles. For example, a mother who would place their child for adoption with a 14% probability if able to inspect more profiles and who observed twenty profiles of identical adoptive families (White, 40 years old, college educated, heterosexual couple) in the first batch would experience a welfare loss of not being able to see additional profiles of -0.0184 pp (s.e. 0.002). If, instead, the mother's probability of placing their child for adoption is 20 percent, the welfare loss is -0.0307 pp (s.e. 0.004). Mothers who have a higher probability of placing their child in adoption face higher welfare losses when their ability to search is restricted.

Table A.2: Order Effect on Adoption Matching

	1	2	3
Order			
2	0.570	0.537	0.578
	(0.183)	(0.254)	(0.249)
3	0.510	0.438	0.530
	(0.174)	(0.229)	(0.221)
4	0.394	0.350	0.490
	(0.149)	(0.214)	(0.213)
5	0.196	0.106	0.277
	(0.092)	(0.090)	(0.148)
6	0.314	0.269	0.355
	(0.124)	(0.162)	(0.180)
7	0.196	0.114	0.274
	(0.089)	(0.084)	(0.139)
8	0.325	0.157	0.552
	(0.132)	(0.112)	(0.245)
9	0.356	0.320	0.528
	(0.142)	(0.208)	(0.239)
10	0.293	0.212	0.432
	(0.119)	(0.149)	(0.199)
11	0.284	0.274	0.406
	(0.118)	(0.180)	(0.203)
12	0.155	0.198	0.184
	(0.073)	(0.140)	(0.119)
13	0.161	0.180	0.224
	(0.078)	(0.136)	(0.131)
14	0.322	0.432	0.447
	(0.133)	(0.285)	(0.205)
15	0.369	0.785	0.290
	(0.144)	(0.477)	(0.158)
16	0.276	0.228	0.489
	(0.121)	(0.183)	(0.231)
17	0.127	0.242	0.096
	(0.068)	(0.179)	(0.078)
18	0.248	0.263	0.498
	(0.107)	(0.186)	(0.236)
19	0.090	0.095	0.142
	(0.053)	(0.082)	(0.100)
20	0.321	0.492	0.313
	(0.127)	(0.351)	(0.144)
Observations	44,226	13,969	6,612
Strata	AF	AF	AF
Intake	Both	Online	Phone

Notes: Stata command clogit used for conditional logit regression. Dependent variable is a dummy variable that equals one if a match occurred. Coefficients are reported as odds ratio. Standard errors in parentheses.

Table A.3: First profile effect on adoption matching

	All	Early	Late
First profile	7.611	8.281	7.011
	(0.118)	(0.208)	(0.145)
Adoptive parents' age	-0.036	-0.036	-0.035
	(0.016)	(0.027)	(0.020)
Black (AP 1)	2.129	-11.614	2.407
	(1.029)	(1705.199)	(1.038)
Hispanic (AP 1)	0.792	-0.026	1.252
	(0.556)	(0.837)	(0.665)
College (AP 1)	-0.760	-1.681	0.029
	(0.594)	(0.721)	(0.841)
Same-sex couple	-0.105	-0.032	-0.146
	(0.434)	(0.736)	(0.532)
Mothers	8154	5216	3021
Profiles	171234	109536	63441

Notes: Conditional Logit regression. Dependent variable is a dummy variable that equals one if a match occurred. The model estimates which profile is chosen among those inspected. The sample is restricted to mothers who only saw 20 profiles. Standard errors are in parentheses. Early are mothers who arrive 12 or more weeks before birth. Late mothers are those who arrive fewer than 12 weeks before birth. Coefficients reported as log odds.

Table A.4: First profile on adoption matching - including those with fewer than 20 profiles

	All	Early	Late
First profile	7.156	8.073	6.466
	(0.092)	(0.184)	(0.107)
Adoptive parents' age	-0.037	-0.045	-0.034
	(0.012)	(0.024)	(0.015)
Black (AP 1)	1.300	-12.891	1.418
	(1.017)	(2463.164)	(1.021)
Hispanic (AP 1)	0.753	0.153	1.010
	(0.427)	(0.748)	(0.508)
College (AP 1)	-0.468	-1.437	0.010
	(0.501)	(0.701)	(0.627)
Same-sex couple	0.278	0.382	0.238
	(0.287)	(0.532)	(0.338)
Mothers	8905	5560	3439
Profiles	180917	114235	68558

Notes: Conditional Logit regression. Dependent variable is a dummy variable that equals one if a match occurred. The model estimates which profile is chosen among those inspected. The sample is restricted to mothers who saw 20 profiles or fewer. Standard errors are in parentheses. Early are mothers who arrive 12 or more weeks before birth. Late mothers are those who arrive fewer than 12 weeks before birth. Coefficients reported as log odds.

Table A.5: Characteristic of mothers by policy changes

	White	Black	Hisp	Age
Trigger ban states after June 24, 2022	0.025	-0.007	-0.001	-0.077
	(0.024)	(0.021)	(0.017)	(0.398)
After June 24, 2022	-0.111	0.103	-0.021	1.386
	(0.013)	(0.011)	(0.009)	(0.213)
Trigger ban states	0.023	0.013	-0.006	-0.524
	(0.011)	(0.010)	(0.008)	(0.152)
Constant	0.513	0.238	0.161	26.194
	(0.006)	(0.005)	(0.004)	(0.081)
Obs	12814	12814	12814	10035

Notes: The dependent variables are whether a birth mother is White, Black, or Hispanic, and the age of the birth mother. The sample is all birth mothers who searched on the agency portal after August 2, 2018.

Table A.6: Dominance test for arrival times

Non-Trigger states	Trigger states
(After FOSD Before, Before FOSD After)	(After FOSD Before, Before FOSD After)
(0.1787,0.2551)	(0.0083,0.4788)

Notes: Regressions are restricted to June 24, 2021-June 23, 2022, and June 24, 2022-June 23, 2023.

Table A.7: Effect of Dobbs on arrival time

	Quantile								
	10	20	30	40	50	60	70	80	90
Trigger ban states after June 24, 2022	-8.478	-10.533	-9.731	-11.692	-15.199	-15.134	-12.394	-4.253	5.101
	(4.358)	(5.402)	(5.738)	(5.991)	(5.676)	(6.058)	(5.874)	(6.778)	(7.764)
After June 24, 2022	-10.396	-10.336	-15.520	-18.718	-16.267	-13.092	-11.637	-14.101	-21.638
	(2.913)	(3.152)	(3.762)	(3.538)	(3.284)	(3.170)	(2.978)	(3.400)	(4.729)
White (mother)	5.392	-2.817	-9.926	-13.146	-13.857	-12.461	-11.691	-11.384	-8.021
	(2.015)	(2.484)	(3.018)	(3.168)	(2.916)	(2.771)	(2.541)	(2.720)	(3.328)
Black (mother)	25.270	32.770	37.471	36.701	29.104	20.957	18.932	19.695	54.736
	(2.616)	(3.242)	(3.756)	(3.412)	(2.823)	(2.805)	(2.849)	(3.036)	(9.620)
Mother's age	-0.191	-0.129	-0.148	-0.154	-0.354	-0.525	-0.527	-0.481	-0.926
	(0.127)	(0.169)	(0.219)	(0.209)	(0.200)	(0.187)	(0.189)	(0.193)	(0.287)
Trigger ban states	5.967	5.510	0.839	-0.908	-0.718	-0.282	-0.054	-3.888	-8.041
	(1.837)	(2.280)	(2.831)	(2.842)	(2.571)	(2.546)	(2.507)	(2.482)	(3.767)
Constant	-240.109	-209.110	-173.690	-142.000	-108.302	-77.465	-52.455	-22.923	29.689
	(3.677)	(4.810)	(6.127)	(6.318)	(5.641)	(5.258)	(5.331)	(5.649)	(9.312)
Obs	12814	12814	12814	12814	12814	12814	12814	12814	12814

Notes: Quantile regressions. Dependent variable is age of child at initial inquiry in days. Standard errors in parentheses. Missing mother's age is replaced with zero and a dummy variable is included for missing data. Results are similar if we include all the data available. Regressions that control for the mothers' characteristics in the whole sample are in Table A.9.

Table A.8: Effect of Dobbs on arrival time - Dench et al. (2024)'s sample

	Quantile								
	10	20	30	40	50	60	70	80	90
Trigger ban states after June 24, 2022	-4.897	-7.153	-9.586	-13.856	-17.929	-14.358	-8.884	2.932	9.402
	(4.260)	(5.260)	(6.907)	(7.197)	(6.285)	(6.511)	(6.009)	(6.589)	(8.576)
After June 24, 2022	-14.515	-14.729	-16.661	-16.492	-12.194	-11.320	-11.313	-17.934	-26.110
	(3.179)	(4.125)	(6.307)	(5.988)	(4.638)	(4.371)	(4.291)	(4.060)	(6.107)
White (mother)	4.648	-3.966	-12.881	-16.866	-15.490	-13.797	-12.887	-13.489	-9.917
	(2.212)	(2.914)	(3.502)	(3.399)	(3.325)	(3.168)	(2.904)	(3.158)	(3.870)
Black (mother)	26.275	35.161	36.128	35.164	29.479	22.192	20.454	22.124	66.988
	(3.126)	(3.827)	(4.356)	(3.860)	(3.020)	(3.108)	(3.377)	(3.806)	(10.588)
Mother's age	-0.235	-0.054	-0.009	-0.008	-0.290	-0.524	-0.532	-0.370	-0.747
	(0.169)	(0.217)	(0.304)	(0.282)	(0.256)	(0.241)	(0.258)	(0.270)	(0.328)
Trigger ban states	8.776	9.406	5.360	0.968	-0.089	-0.760	-2.633	-7.086	-12.086
	(1.991)	(2.679)	(3.200)	(3.114)	(2.793)	(2.910)	(3.002)	(3.053)	(4.343)
Constant	-241.101	-213.500	-178.214	-143.588	-108.685	-76.134	-49.039	-21.712	30.087
	(4.417)	(6.463)	(8.229)	(7.792)	(7.259)	(6.991)	(7.364)	(7.717)	(10.869)
Obs	8493	8493	8493	8493	8493	8493	8493	8493	8493

Notes: Quantile regressions. Dependent variable is age of child at initial inquiry in days. Standard errors in parentheses. Missing mother's age is replaced with zero and a dummy variable is included for missing data. Results are similar if we include all the data available. Regressions that control for the mothers' characteristics in the whole sample are in Table A.7. The sample excludes Arizona, Florida, Georgia, Indiana, Iowa, Nebraska, North Carolina, North Dakota, Ohio, Pensylvannia, South carolina, Utah and Wyoming. Texas is considered "treated" since September 1, 2021.

Table A.9: Effect of Dobbs on arrival time - unrestricted sample

	QUANTILE								
	10	20	30	40	50	60	70	80	90
Trigger ban states after June 24, 2022	-5.800	-5.393	-5.922	-6.943	-10.964	-11.599	-8.103	-2.216	9.817
	(4.026)	(4.476)	(4.916)	(5.435)	(5.036)	(5.715)	(5.620)	(5.821)	(5.626)
After June 24, 2022	-14.551	-14.879	-16.088	-16.803	-13.613	-10.686	-8.628	-8.916	-16.205
	(2.654)	(2.500)	(3.064)	(3.156)	(2.878)	(2.825)	(2.718)	(2.596)	(3.937)
White (mother)	0.401	-7.763	-14.204	-17.999	-18.733	-16.395	-15.290	-14.594	-10.794
	(1.142)	(1.521)	(1.882)	(1.851)	(1.825)	(1.773)	(1.712)	(1.712)	(2.076)
Black (mother)	26.042	37.029	41.247	40.076	34.683	29.688	25.233	20.426	26.826
	(2.110)	(2.291)	(2.428)	(2.185)	(1.796)	(1.804)	(1.767)	(1.816)	(4.743)
Mother's age	-0.078	-0.033	-0.073	-0.032	-0.102	-0.078	-0.045	-0.001	-0.075
	(0.055)	(0.078)	(0.086)	(0.096)	(0.088)	(0.091)	(0.086)	(0.088)	(0.108)
Trigger ban states	2.509	0.967	-3.053	-4.052	-3.436	-2.729	-2.326	-3.679	-7.688
	(1.129)	(1.388)	(1.527)	(1.596)	(1.580)	(1.625)	(1.495)	(1.387)	(2.118)
Constant	-232.279	-201.844	-169.277	-141.756	-114.603	-91.500	-68.348	-42.568	-6.211
	(1.472)	(2.152)	(2.605)	(2.889)	(2.560)	(2.439)	(2.433)	(2.323)	(2.879)
Obs	30767	30767	30767	30767	30767	30767	30767	30767	30767

Notes: Quantile regressions. Dependent variable is age of child at initial inquiry in days. Standard errors in parentheses. Missing mother's age is replaced with zero and a dummy variable is included for missing data. Data is from 2005-June 2023.

Table A.10: Effect of Dobbs on arrival time - Placebo regression

	QUANTILE								
	10	20	30	40	50	60	70	80	90
Trigger ban states after June 24, 2021	-2.219	-7.558	-5.731	-7.863	-0.416	1.649	7.906	13.929	15.037
	(4.986)	(5.340)	(6.443)	(7.195)	(6.903)	(6.860)	(7.535)	(6.810)	(9.026)
After June 24, 2021	-17.900	-14.835	-19.110	-16.303	-12.330	-8.541	-6.946	-4.821	-3.120
	(2.608)	(3.048)	(3.610)	(3.622)	(3.363)	(3.211)	(3.173)	(4.052)	(4.505)
White (mother)	4.380	-3.570	-11.303	-16.181	-15.718	-13.717	-12.690	-13.260	-7.652
	(1.855)	(2.919)	(3.202)	(3.432)	(3.137)	(2.759)	(2.732)	(3.049)	(4.043)
Black (mother)	34.064	45.129	51.584	45.832	36.072	27.479	25.235	25.336	79.281
	(3.494)	(4.429)	(4.032)	(3.573)	(3.016)	(3.112)	(3.466)	(3.963)	(9.145)
Mother's age	-0.053	0.075	0.137	0.095	-0.141	-0.349	-0.425	-0.429	-0.703
	(0.124)	(0.178)	(0.252)	(0.234)	(0.204)	(0.203)	(0.222)	(0.233)	(0.299)
Trigger ban states	6.681	6.720	1.766	-0.090	-0.840	-0.701	-1.633	-6.406	-11.685
	(2.025)	(2.670)	(3.021)	(2.654)	(2.628)	(2.803)	(2.731)	(2.867)	(4.539)
Constant	-240.744	-212.601	-179.435	-146.932	-113.677	-82.359	-55.548	-25.257	18.964
	(3.704)	(5.317)	(7.057)	(7.108)	(6.116)	(5.977)	(6.357)	(6.568)	(8.949)
Obs	10114	10114	10114	10114	10114	10114	10114	10114	10114

Notes: Quantile regressions. Dependent variable is age of child at initial inquiry in days. Standard errors in parentheses. Missing mother's age is replaced with zero and a dummy variable is included for missing data. Data after June 24, 2022 are dropped. Dobbs is assumed to have occurred a year earlier.

Table A.11: Effect of Dobbs on arrival time - Placebo regression (incl. Texas dummy variable)

	Quantile								
	10	20	30	40	50	60	70	80	90
Trigger ban states after June 24, 2021	-4.032	-9.219	-6.949	-8.924	-1.607	1.349	10.857	21.124	23.050
	(5.944)	(6.625)	(7.797)	(8.580)	(8.624)	(8.016)	(9.322)	(8.528)	(11.218)
After June 24, 2021	-17.934	-14.850	-19.144	-16.318	-12.402	-8.613	-6.944	-4.817	-3.148
	(2.623)	(3.060)	(3.593)	(3.591)	(3.358)	(3.234)	(3.173)	(4.035)	(4.537)
White (mother)	4.274	-3.971	-12.150	-17.018	-16.961	-14.818	-13.345	-13.913	-8.644
	(1.835)	(3.069)	(3.370)	(3.516)	(3.198)	(2.933)	(2.825)	(3.008)	(4.255)
Black (mother)	34.030	44.866	50.991	45.061	35.281	26.706	24.641	24.669	78.196
	(3.453)	(4.425)	(4.012)	(3.650)	(3.071)	(3.081)	(3.487)	(3.888)	(9.529)
Mother's age	-0.049	0.078	0.136	0.080	-0.131	-0.340	-0.414	-0.405	-0.697
	(0.121)	(0.176)	(0.252)	(0.235)	(0.208)	(0.207)	(0.222)	(0.238)	(0.296)
Trigger ban states	7.358	8.047	4.245	3.224	2.987	2.335	-0.092	-4.874	-8.600
	(2.266)	(3.132)	(3.543)	(3.450)	(3.337)	(3.292)	(3.094)	(3.296)	(5.021)
Texas	-1.975	-3.710	-6.990	-8.587	-10.315	-8.860	-4.835	-3.884	-9.457
	(3.523)	(4.492)	(5.372)	(4.907)	(5.274)	(5.422)	(5.232)	(4.617)	(7.848)
Texas after June 24, 2021	5.984	4.587	3.598	2.219	2.721	1.009	-6.373	-16.656	-24.340
	(9.102)	(8.765)	(10.404)	(12.852)	(14.487)	(12.563)	(12.888)	(11.464)	(13.734)
Constant	-240.757	-212.409	-178.834	-145.865	-113.118	-81.856	-55.371	-25.393	19.592
	(3.688)	(5.437)	(7.100)	(7.127)	(6.167)	(6.025)	(6.294)	(6.541)	(9.154)
Obs	10114	10114	10114	10114	10114	10114	10114	10114	10114

Notes: Quantile regressions. Dependent variable is age of child at initial inquiry in days. Standard errors in parentheses. Missing mother's age is replaced with zero and a dummy variable is included for missing data. Data after June 24, 2022 are dropped. Dobbs is assumed to have occurred a year earlier.

Table A.12: Changes-in-changes

Specification	Effect on mean (s.e.)
Unconditional	-9.49 (4.74)
Residualized	-5.85 (5.34)

Notes: Athey and Imbens (2006) changes-in-changes regression. Dependent variable is age of child at arrival.

Table A.13: Effect of Dobbs on arrival time - Black mothers

	Quantile								
	10	20	30	40	50	60	70	80	90
Trigger ban states after June 24, 2022	-12.066	-19.816	-13.624	-20.934	-25.454	-28.126	-27.580	-18.646	26.812
	(8.394)	(10.676)	(10.814)	(9.310)	(8.187)	(8.763)	(9.542)	(10.567)	(25.101)
After June 24, 2022	-32.539	-36.579	-50.293	-44.466	-38.166	-30.796	-27.192	-29.873	-79.732
	(6.675)	(8.201)	(6.618)	(4.748)	(4.615)	(4.894)	(5.736)	(5.796)	(14.692)
Mother's age	-0.639	-0.627	0.086	-0.197	-0.445	-0.800	-1.026	-1.169	-2.336
	(0.450)	(0.527)	(0.517)	(0.403)	(0.320)	(0.343)	(0.396)	(0.480)	(0.942)
Trigger ban states	8.635	-0.270	-9.427	-6.299	-3.395	-3.398	-4.785	-10.777	-42.105
	(5.511)	(6.122)	(6.106)	(4.410)	(3.302)	(3.648)	(4.371)	(5.088)	(20.350)
Constant	-199.025	-154.092	-129.812	-96.163	-71.669	-44.376	-15.219	21.681	153.044
	(11.271)	(12.801)	(13.434)	(10.368)	(8.488)	(9.251)	(10.390)	(13.135)	(25.297)
Obs	3370	3370	3370	3370	3370	3370	3370	3370	3370

Notes: Quantile regressions. Dependent variable is age of child at initial inquiry in days. Standard errors in parentheses. Missing mother's age is replaced with zero and a dummy variable is included for missing data.

Table A.14: Effect of Dobbs on arrival time - Hispanic mothers

	QUANTILE								
	10	20	30	40	50	60	70	80	90
Trigger ban states after June 24, 2022	-5.522	-4.767	-10.774	-21.436	-26.901	-19.224	-13.306	-3.299	13.085
	(14.071)	(12.745)	(12.237)	(14.388)	(17.061)	(17.528)	(15.208)	(18.311)	(16.701)
After June 24, 2022	3.402	5.160	0.280	-0.038	3.148	1.733	-1.862	-6.638	-12.229
	(7.115)	(8.526)	(9.043)	(9.327)	(7.932)	(6.947)	(7.663)	(8.689)	(9.843)
Mother's age	-0.003	0.162	0.229	-0.087	-0.376	-0.427	-0.606	-0.942	-1.026
	(0.355)	(0.447)	(0.581)	(0.563)	(0.507)	(0.455)	(0.465)	(0.542)	(0.655)
Trigger ban states	7.592	7.835	4.105	2.713	2.209	3.062	3.744	0.131	-6.084
	(4.911)	(5.844)	(6.732)	(7.241)	(6.620)	(6.589)	(6.116)	(6.266)	(8.821)
Constant	-245.131	-219.427	-189.412	-150.927	-116.205	-89.378	-58.533	-19.347	22.947
	(8.764)	(11.912)	(16.209)	(16.466)	(14.228)	(12.928)	(13.033)	(14.505)	(18.720)
Obs	1988	1988	1988	1988	1988	1988	1988	1988	1988

Notes: Quantile regressions. Dependent variable is age of child at initial inquiry in days. Standard errors in parentheses. Missing mother's age is replaced with zero and a dummy variable is included for missing data.

Table A.15: Effect of Dobbs on arrival time - White mothers

	QUANTILE								
	10	20	30	40	50	60	70	80	90
Trigger ban states after June 24, 2022	-3.031	-7.129	-6.319	-5.880	-8.191	-6.102	-6.999	-6.066	-2.239
	(5.194)	(7.024)	(8.653)	(8.412)	(9.808)	(8.743)	(8.066)	(7.780)	(8.784)
After June 24, 2022	-2.099	1.036	1.753	-0.266	-1.306	-1.937	-1.238	-1.066	-6.651
	(3.284)	(4.509)	(4.791)	(4.802)	(5.916)	(5.147)	(5.227)	(4.973)	(5.532)
Mother's age	0.132	0.082	-0.008	0.071	-0.141	-0.288	-0.155	-0.018	-0.294
	(0.148)	(0.182)	(0.246)	(0.262)	(0.296)	(0.275)	(0.262)	(0.261)	(0.314)
Trigger ban states	2.432	4.546	2.639	0.611	1.667	1.579	2.321	1.200	-0.806
	(2.132)	(2.951)	(3.565)	(3.974)	(4.310)	(3.933)	(3.376)	(3.592)	(4.095)
Constant	-242.961	-218.329	-189.421	-164.205	-130.989	-98.216	-75.585	-49.303	-0.541
	(4.195)	(5.402)	(6.920)	(7.416)	(8.307)	(8.016)	(7.428)	(7.791)	(9.487)
Obs	6377	6377	6377	6377	6377	6377	6377	6377	6377

Notes: Quantile regressions. Dependent variable is age of child at initial inquiry in days. Standard errors in parentheses. Missing mother's age is replaced with zero and a dummy variable is included for missing data.

B Decision Attention

B.1 Evidence of quasi-random ordering

We identify that every birth mother who signed up with our partner adoption agency during our sample period through the online intake form or calling the adoption agency received a quasi-randomly ordered list of waiting adoptive families. When a birth mother reaches out to our partner, they fill out an inquiry form containing basic demographic and contact information. Within several minutes of filling out their information, a birth mother receives a welcome email containing a list of up to 20 waiting adoptive families.[1] These families are selected based on their characteristics and preferences for a birth mother, as well as the characteristics and preferences of the birth mother for an adoptive family.

Beginning on August 1st of 2018, our partner altered the birth mother intake form to reduce the information collected at the inquiry stage. Adoptive families were then selected to be placed on a birth mother's welcome email based on having consistent preferences for the expected race of the baby and residing in a state that allows interstate adoption with the birth mother's state of residence.[2] This policy change resulted in an increase in the number of adoptive families eligible to be shown in a birth mother's welcome email. To order the eligible adoptive family profiles within the welcome email, the agency used an alphabetical ordering mechanism based on the first name of the adoptive parents.[3] Assuming an orthogonal relationship between the first name used for ordering and an adoption family's characteristics and preferences, we can identify quasi-random variation in the welcome email which we then use to understand the decision attention of birth mothers in the adoption process.

[1] See Figure B.1. Birth mothers receive up to 20 adoptive family profiles in the welcome email. The total number is determined based on the number of adoptive families available and their stated preferences.

[2] The interstate adoption laws are based on state-level ICPC legislation. The ability for our partner agency to assist in adoption services across states will depend on their licensure and ability to provide a home study in that particular state.

[3] Specifically, in heterosexual couples this would be the male's first name and in same-sex couples this would be whichever partner had the earlier alphabetically ordered first name.

We verify the viability of the alphabetical ordering assignment mechanism as an instrument to measure decision attention. Figure B.2 shows the average order of each letter of the adoptive parent's first name. In order to provide a consistent comparisons across welcome emails, the sample is restricted to heterosexual couples and to observations that were in a welcome email with 20 distinct profiles. For heterosexual couples, adoptive parent 1's (or the male spouse's) first name is highly predictive of the average position in the welcome email (p-value=0.000). Adoptive families with early alphabetical male first names are, on average, shown earlier in the welcome email than adoptive families with later alphabetical male first names. The average position of an adoptive family profile in the welcome email based on the adoptive parent 2's (or the female spouse's) first name is insignificantly predictive of the average position of a family's profile in the welcome email (p-value=0.179). Our results confirm that profiles in the welcome email that birth mothers receive are ordered by the adoptive parent 1's first name.

As profiles are ordered alphabetically based on the first name of the first adoptive parent, adoptive families should be, on average, the same in any order position within the welcome email. This would imply that any systematic preference for a particular position, on average, is due to the position itself rather than the characteristics of the adoptive family in that position. We test the assumption of independence of adoptive family characteristics across orders to validate the exogeneity of our instrument. Tables B.1, B.2, B.3, and B.4 report adoptive family covariates regressed on the order in which a profile is positioned in the welcome email. This results in 17 regressions on 19 order covariates. The first order position is the excluded order. The coefficients represent the difference between the mean order value and the mean value of order 1. Clustered standard errors are displayed in parentheses, and their p-values are shown in square brackets. We use the Romano and Wolf (RW) corrected standard errors to account for multiple hypothesis testing (List et al., 2019). The subsequent RW p-values are listed beneath the coefficients, clustered standard errors, and p-values in angle brackets. The results demonstrate no significant relationship between the

order in which the adoptive family appears in the welcome email and any adoptive family characteristic. Our results support the validity of using order as a quasi-random assignment instrument.

The implication of finding a valid instrument is that it allows us to test for particular behavioral features driven by the design of the email itself. The email structure creates a sequential view of adoptive families for birth mothers, where birth mothers must scroll through profiles in order, starting at the top (the first order). Since adoptive families are quasi-randomly assigned to positions and each position contains, on average, similar profiles, any systematic preference for particular positions must reflect the order itself rather than the family characteristics. Specifically, if birth mothers exhibit disproportionate selection of early ordered profiles, this would reveal attention patterns in decision-making. This sequential structure allows us to measure birth mother attention by examining how the probability of adoption placement varies across order positions. These findings on decision attention are developed in Section 4.3.

B.2 Characterizing mothers affected by order

We provide descriptive evidence of the mothers affected by the order in which adoptive families are presented in the welcome email and then examine effects of the Dobbs decision. Analysis is restricted to the first twenty profiles shown. We consider the mother-adoptive family pair as the unit of analysis. The treatment (Z) is to appear in order 1-10, and not treated is to appear in order 11-20. Treatment status (D) equals one if a match occurs and zero if not. To identify characteristics of complier mothers, i.e., those who reacted to the order of the profile, we estimate the effect of D on $X \times D$ using Z as an instrument where X is a mother's characteristic. Regressions are run separately for each characteristics, and errors are clustered at the mother level.

Table B.5 presents these results.[4] Columns (1) and (2) confirm that those responding

[4]The table characterizes compliers, i.e. those who change a decision due to order effects. This is done by

to the order of the profile tend to be late in their pregnancy (-32.3 v. -114.3 days). Those affected by the profile order are less likely to be Black, more likely to be White and older. Columns (3)-(6) show that non-White mothers reacting to the order of the profile are earlier in their pregnancy than White mothers (-72.7 v. -6.1 days). Relatively older non-White mothers explain the age effect on the whole population. We find that the reduction in the frequency of compliers in trigger states after the Dobbs decision (-0.118) is due to Non-White mothers (-0.192). Among White mothers, there is a slight decrease of compliers in trigger states after the Dobbs decision, but this is noisy. The table also shows the difference in the budget allocated to the birth mother by the adoptive family. Mothers more likely to choose a family when presented earlier receive over five thousand dollars less to cover pregnancy costs. We cannot determine if this is due to time-to-birth considerations or bargaining between parties. The last row in the table shows that, on average, these mothers are matched with families with lower income.

comparing adoptions and the order of the list. We report heterogeneity by White and Non-white mothers without further disaggregation. Since the probability of adoption is low and the probability of changing behavior due to order effects is even smaller, further disaggregation would result in noisy estimates.

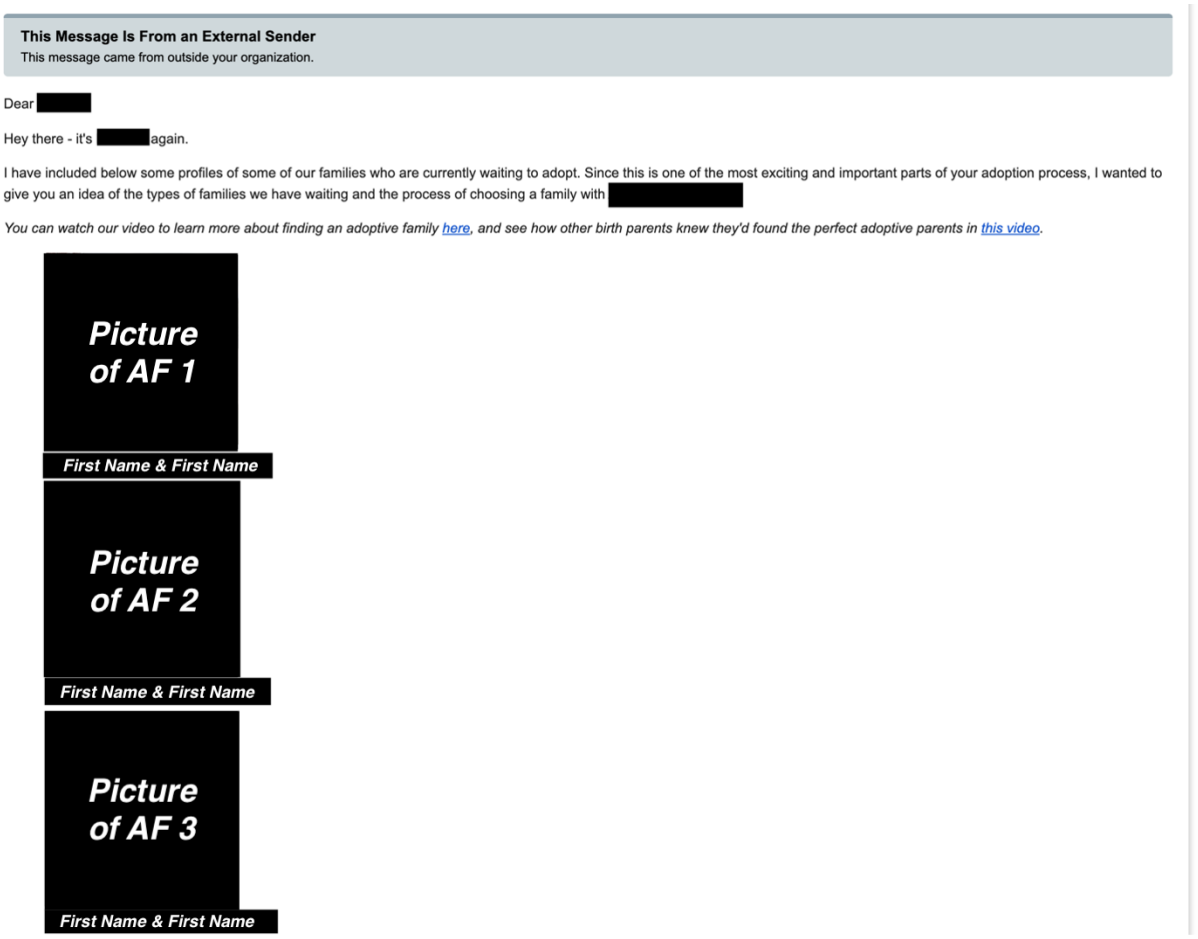
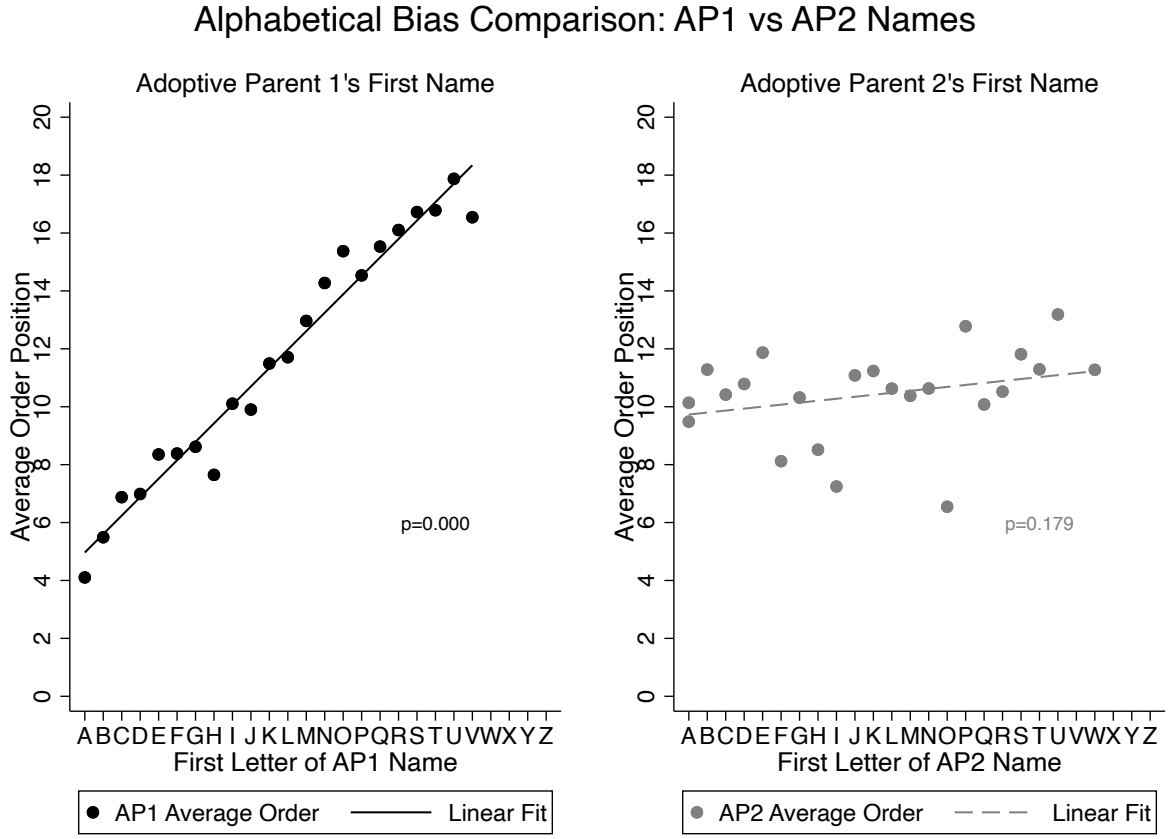


Figure B.1: Example of Welcome Email

Notes: After submitting an initial inquiry, the birth mother receives a confirmation email acknowledging that the inquiry was received. Subsequently, the birth mother receives the email above.



Notes: The figure documents the average position an adoptive family is shown in the welcome email based on the first letter of each adoptive parent's first name. We limit our sample to heterosexual couples that are shown in a welcome email containing 20 distinct AF profiles to simplify our comparison.

Figure B.2: Average Order of Adoptive Family Profiles in Welcome Email by First Names Initial

Table B.1: Regression of Adoptive Family Covariates on Order (Part 1)

	Family Budget	Family Salary	White Family	Black Family	Hispanic Family	Mixed-race Family	Heterosexual Couple	Same-sex Couple
Order 2	-53.923	-6,183	0.021	-0.000	-0.008	-0.019	0.005	-0.005
	(515.318)	(4,999)	(0.022)	(0.000)	(0.008)	(0.020)	(0.014)	(0.014)
	[0.917]	[0.216]	[0.331]	[0.542]	[0.338]	[0.338]	[0.716]	[0.713]
	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩
Order 3	166.982	-6,924	0.034	-0.000	-0.014	-0.023	0.008	-0.008
	(671.284)	(6,301)	(0.029)	(0.000)	(0.009)	(0.026)	(0.017)	(0.017)
	[0.804]	[0.272]	[0.237]	[0.354]	[0.132]	[0.391]	[0.658]	[0.627]
	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨0.976⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩
Order 4	423.013	-7,104	0.036	0.001	-0.016	-0.017	0.007	-0.008
	(759.014)	(6,969)	(0.032)	(0.001)	(0.010)	(0.029)	(0.019)	(0.019)
	[0.577]	[0.308]	[0.254]	[0.535]	[0.129]	[0.570]	[0.704]	[0.680]
	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨0.970⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩
Order 5	210.047	-5,341	0.053	0.001	-0.019	-0.027	0.001	-0.001
	(763.601)	(7,321)	(0.033)	(0.002)	(0.011)	(0.030)	(0.020)	(0.020)
	[0.783]	[0.466]	[0.107]	[0.452]	[0.105]	[0.368]	[0.980]	[0.942]
	⟨1.000⟩	⟨1.000⟩	⟨0.950⟩	⟨1.000⟩	⟨0.947⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩
Order 6	230.532	-1,890	0.052	0.003	-0.020	-0.023	0.002	-0.004
	(769.537)	(7,694)	(0.034)	(0.003)	(0.012)	(0.031)	(0.020)	(0.020)
	[0.765]	[0.806]	[0.125]	[0.321]	[0.081]	[0.457]	[0.906]	[0.846]
	⟨1.000⟩	⟨1.000⟩	⟨0.964⟩	⟨1.000⟩	⟨0.907⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩
Order 7	208.158	1,345	0.043	0.006	-0.020	-0.016	-0.002	-0.001
	(754.339)	(7,735)	(0.034)	(0.006)	(0.012)	(0.031)	(0.021)	(0.021)
	[0.783]	[0.862]	[0.207]	[0.288]	[0.081]	[0.603]	[0.909]	[0.979]
	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨0.909⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩
Order 8	-17.678	6,122	0.047	0.007	-0.017	-0.023	-0.008	0.005
	(750.094)	(7,929)	(0.034)	(0.007)	(0.012)	(0.030)	(0.021)	(0.021)
	[0.981]	[0.440]	[0.165]	[0.284]	[0.148]	[0.456]	[0.692]	[0.825]
	⟨1.000⟩	⟨1.000⟩	⟨0.990⟩	⟨1.000⟩	⟨0.983⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩
Order 9	-44.658	8,564	0.051	0.006	-0.016	-0.025	-0.008	0.001
	(737.019)	(7,803)	(0.033)	(0.005)	(0.012)	(0.030)	(0.021)	(0.021)
	[0.952]	[0.273]	[0.129]	[0.230]	[0.190]	[0.402]	[0.714]	[0.948]
	⟨1.000⟩	⟨1.000⟩	⟨0.970⟩	⟨1.000⟩	⟨0.998⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩
Order 10	-108.613	10,980	0.059	0.005	-0.014	-0.029	-0.012	0.005
	(743.049)	(7,940)	(0.033)	(0.004)	(0.012)	(0.030)	(0.021)	(0.021)
	[0.884]	[0.167]	[0.069]	[0.194]	[0.233]	[0.331]	[0.568]	[0.815]
	⟨1.000⟩	⟨0.991⟩	⟨0.869⟩	⟨0.998⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩
Order 11	23.681	10,894	0.076	0.003	-0.013	-0.044	-0.010	0.004
	(748.571)	(7,859)	(0.032)	(0.003)	(0.012)	(0.030)	(0.021)	(0.021)
	[0.975]	[0.166]	[0.019]	[0.165]	[0.297]	[0.141]	[0.626]	[0.848]
	⟨1.000⟩	⟨0.991⟩	⟨0.649⟩	⟨0.990⟩	⟨1.000⟩	⟨0.981⟩	⟨1.000⟩	⟨1.000⟩
Order 1 Mean	46,914.543	185,301.987	0.735	0.002	0.027	0.202	0.906	0.093
Observations	353,151	320,151	353,151	353,151	353,151	353,151	353,151	353,151

Notes: Each column reports coefficients from OLS regression of the covariate on order indicators (Order 1 omitted). Standard errors in parentheses, uncorrected p-values in brackets, Romano-Wolf corrected p-values in angle brackets. Standard errors clustered by family ID.

Table B.2: Regression of Adoptive Family Covariates on Order (Part 2)

	Family Budget	Family Salary	White Family	Black Family	Hispanic Family	Mixed-race Family	Heterosexual Couple	Same-sex Couple
Order 12	303.317	16,211	0.078	0.002	-0.014	-0.044	-0.011	0.003
	(746.697)	(8,188)	(0.032)	(0.002)	(0.012)	(0.029)	(0.022)	(0.021)
	[0.685]	[0.048]	[0.016]	[0.334]	[0.238]	[0.131]	[0.626]	[0.875]
	⟨1.000⟩	⟨0.807⟩	⟨0.631⟩	⟨1.000⟩	⟨1.000⟩	⟨0.976⟩	⟨1.000⟩	⟨1.000⟩
Order 13	724.364	18,766	0.072	0.001	-0.013	-0.047	-0.013	0.006
	(765.612)	(8,486)	(0.033)	(0.002)	(0.012)	(0.030)	(0.022)	(0.021)
	[0.344]	[0.027]	[0.028]	[0.385]	[0.267]	[0.118]	[0.563]	[0.772]
	⟨1.000⟩	⟨0.698⟩	⟨0.707⟩	⟨1.000⟩	⟨1.000⟩	⟨0.960⟩	⟨1.000⟩	⟨1.000⟩
Order 14	1477.715	25,438	0.068	-0.000	-0.013	-0.048	-0.007	-0.000
	(983.257)	(9,508)	(0.034)	(0.001)	(0.012)	(0.030)	(0.021)	(0.021)
	[0.133]	[0.008]	[0.043]	[0.873]	[0.293]	[0.109]	[0.749]	[0.999]
	⟨0.976⟩	⟨0.548⟩	⟨0.786⟩	⟨1.000⟩	⟨1.000⟩	⟨0.950⟩	⟨1.000⟩	⟨1.000⟩
Order 15	1950.884	22,959	0.067	-0.000	-0.012	-0.057	0.003	-0.007
	(1337.746)	(9,528)	(0.034)	(0.001)	(0.012)	(0.030)	(0.021)	(0.020)
	[0.145]	[0.016]	[0.051]	[0.891]	[0.338]	[0.053]	[0.897]	[0.738]
	⟨0.982⟩	⟨0.626⟩	⟨0.817⟩	⟨1.000⟩	⟨1.000⟩	⟨0.823⟩	⟨1.000⟩	⟨1.000⟩
Order 16	1779.741	23,513	0.063	-0.000	-0.015	-0.058	0.007	-0.009
	(1167.246)	(9,638)	(0.035)	(0.001)	(0.012)	(0.030)	(0.021)	(0.021)
	[0.127]	[0.015]	[0.070]	[0.530]	[0.202]	[0.055]	[0.725]	[0.657]
	⟨0.967⟩	⟨0.614⟩	⟨0.875⟩	⟨1.000⟩	⟨0.999⟩	⟨0.831⟩	⟨1.000⟩	⟨1.000⟩
Order 17	1345.881	20,269	0.050	-0.000	-0.018	-0.045	0.012	-0.013
	(929.862)	(9,289)	(0.035)	(0.001)	(0.012)	(0.031)	(0.022)	(0.022)
	[0.148]	[0.029]	[0.156]	[0.605]	[0.147]	[0.149]	[0.586]	[0.564]
	⟨0.983⟩	⟨0.712⟩	⟨0.985⟩	⟨1.000⟩	⟨0.982⟩	⟨0.983⟩	⟨1.000⟩	⟨1.000⟩
Order 18	1019.242	17,336	0.054	-0.000	-0.021	-0.039	0.018	-0.017
	(854.966)	(9,027)	(0.036)	(0.001)	(0.012)	(0.033)	(0.022)	(0.022)
	[0.233]	[0.055]	[0.131]	[0.747]	[0.077]	[0.237]	[0.412]	[0.434]
	⟨1.000⟩	⟨0.831⟩	⟨0.976⟩	⟨1.000⟩	⟨0.898⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩
Order 19	1172.437	8,189	0.065	-0.000	-0.023	-0.036	0.008	-0.008
	(910.297)	(9,395)	(0.038)	(0.001)	(0.012)	(0.036)	(0.027)	(0.027)
	[0.198]	[0.383]	[0.092]	[0.541]	[0.054]	[0.317]	[0.755]	[0.776]
	⟨0.998⟩	⟨1.000⟩	⟨0.927⟩	⟨1.000⟩	⟨0.829⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩
Order 20	892.763	147	0.050	0.001	-0.017	-0.024	-0.012	0.013
	(1171.610)	(10,906)	(0.047)	(0.002)	(0.014)	(0.044)	(0.038)	(0.038)
	[0.446]	[0.989]	[0.292]	[0.549]	[0.213]	[0.580]	[0.742]	[0.726]
	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩
Order 1 Mean	46,914.543	185,301.987	0.735	0.002	0.027	0.202	0.906	0.093
Observations	353,151	320,151	353,151	353,151	353,151	353,151	353,151	353,151

Notes: Each column reports coefficients from OLS regression of the covariate on order indicators (Order 1 omitted). Standard errors in parentheses, uncorrected p-values in brackets, Romano-Wolf corrected p-values in angle brackets. Standard errors clustered by family ID.

Table B.3: Balance Test: Regression of Adoptive Family Covariates on Order (Part 3)

	Urban Residence	Rural Residence	Suburban Residence	AP1 Age	AP2 Age	Preference White Baby	Preference Black Baby	Preference Hispanic Baby	Preference Baby Gender
Order 2	-0.016	0.018	-0.003	0.203	0.132	-0.007	0.002	-0.015	-0.003
	(0.027)	(0.014)	(0.028)	(0.265)	(0.247)	(0.021)	(0.025)	(0.021)	(0.004)
	[0.558]	[0.172]	[0.925]	[0.444]	[0.593]	[0.726]	[0.920]	[0.476]	[0.451]
	⟨1.000⟩	⟨0.995⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩
Order 3	-0.013	0.021	-0.008	0.275	0.285	-0.011	-0.004	-0.006	-0.003
	(0.034)	(0.021)	(0.036)	(0.367)	(0.328)	(0.029)	(0.033)	(0.029)	(0.005)
	[0.700]	[0.322]	[0.828]	[0.453]	[0.385]	[0.715]	[0.890]	[0.847]	[0.473]
	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩
Order 4	-0.018	0.027	-0.009	0.585	0.477	-0.016	-0.017	-0.006	-0.003
	(0.036)	(0.024)	(0.039)	(0.401)	(0.365)	(0.032)	(0.036)	(0.032)	(0.005)
	[0.625]	[0.270]	[0.817]	[0.145]	[0.191]	[0.617]	[0.635]	[0.845]	[0.506]
	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨0.982⟩	⟨0.998⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩
Order 5	-0.023	0.034	-0.010	0.666	0.516	-0.009	-0.016	-0.000	-0.005
	(0.035)	(0.026)	(0.039)	(0.414)	(0.390)	(0.031)	(0.037)	(0.031)	(0.005)
	[0.508]	[0.188]	[0.789]	[0.108]	[0.186]	[0.759]	[0.664]	[0.991]	[0.356]
	⟨1.000⟩	⟨0.998⟩	⟨1.000⟩	⟨0.950⟩	⟨0.998⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩
Order 6	-0.042	0.036	0.006	0.882	0.617	-0.004	-0.026	0.002	-0.006
	(0.034)	(0.026)	(0.039)	(0.422)	(0.402)	(0.031)	(0.038)	(0.031)	(0.005)
	[0.219]	[0.161]	[0.870]	[0.036]	[0.125]	[0.891]	[0.491]	[0.953]	[0.270]
	⟨1.000⟩	⟨0.988⟩	⟨1.000⟩	⟨0.751⟩	⟨0.964⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩
Order 7	-0.043	0.032	0.011	1.032	0.690	-0.006	-0.028	0.001	-0.005
	(0.034)	(0.024)	(0.038)	(0.426)	(0.407)	(0.031)	(0.038)	(0.031)	(0.005)
	[0.206]	[0.188]	[0.775]	[0.015]	[0.090]	[0.849]	[0.453]	[0.970]	[0.337]
	⟨1.000⟩	⟨0.998⟩	⟨1.000⟩	⟨0.620⟩	⟨0.925⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩
Order 8	-0.045	0.026	0.019	1.034	0.595	0.004	-0.029	0.003	-0.005
	(0.034)	(0.024)	(0.038)	(0.426)	(0.404)	(0.030)	(0.038)	(0.031)	(0.005)
	[0.188]	[0.287]	[0.611]	[0.015]	[0.142]	[0.901]	[0.438]	[0.934]	[0.323]
	⟨0.998⟩	⟨1.000⟩	⟨1.000⟩	⟨0.618⟩	⟨0.981⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩
Order 9	-0.035	0.031	0.004	0.967	0.520	0.005	-0.033	0.002	-0.008
	(0.035)	(0.024)	(0.039)	(0.429)	(0.402)	(0.030)	(0.038)	(0.031)	(0.005)
	[0.306]	[0.204]	[0.910]	[0.024]	[0.196]	[0.871]	[0.374]	[0.937]	[0.091]
	⟨1.000⟩	⟨0.999⟩	⟨1.000⟩	⟨0.690⟩	⟨0.998⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨0.926⟩
Order 10	-0.026	0.035	-0.009	0.803	0.382	0.016	-0.034	0.007	-0.010
	(0.035)	(0.024)	(0.039)	(0.423)	(0.397)	(0.029)	(0.038)	(0.031)	(0.005)
	[0.454]	[0.149]	[0.819]	[0.058]	[0.335]	[0.591]	[0.364]	[0.821]	[0.024]
	⟨1.000⟩	⟨0.983⟩	⟨1.000⟩	⟨0.842⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨0.690⟩
Order 11	-0.019	0.040	-0.022	0.762	0.318	0.016	-0.033	0.007	-0.009
	(0.036)	(0.026)	(0.040)	(0.420)	(0.396)	(0.030)	(0.038)	(0.031)	(0.005)
	[0.603]	[0.119]	[0.585]	[0.070]	[0.422]	[0.585]	[0.384]	[0.832]	[0.064]
	⟨1.000⟩	⟨0.960⟩	⟨1.000⟩	⟨0.874⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨0.862⟩
Order 1 Mean	0.199	0.081	0.720	38.217	37.762	0.815	0.619	0.775	0.016
Observations	325,731	325,731	325,731	353,151	353,151	352,443	352,443	352,443	353,151

Notes: Each column reports coefficients from OLS regression of the covariate on order indicators (Order 1 omitted). Standard errors in parentheses, uncorrected p-values in brackets, Romano-Wolf corrected p-values in angle brackets. Standard errors clustered by family ID.

Table B.4: Balance Test: Regression of Adoptive Family Covariates on Order (Part 4)

	Urban Residence	Rural Residence	Suburban Residence	AP1 Age	AP2 Age	Preference White Baby	Preference Black Baby	Preference Hispanic Baby	Preference Baby Gender
Order 12	-0.014	0.045	-0.031	0.594	0.178	0.013	-0.031	0.010	-0.010
	(0.036)	(0.027)	(0.040)	(0.415)	(0.392)	(0.031)	(0.038)	(0.032)	(0.004)
	[0.697]	[0.091]	[0.441]	[0.153]	[0.650]	[0.673]	[0.409]	[0.753]	[0.027]
	⟨1.000⟩	⟨0.926⟩	⟨1.000⟩	⟨0.984⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨0.698⟩
Order 13	-0.001	0.050	-0.049	0.669	0.285	0.011	-0.036	0.017	-0.009
	(0.036)	(0.028)	(0.041)	(0.420)	(0.401)	(0.032)	(0.038)	(0.032)	(0.005)
	[0.979]	[0.074]	[0.232]	[0.111]	[0.477]	[0.726]	[0.346]	[0.598]	[0.062]
	⟨1.000⟩	⟨0.883⟩	⟨1.000⟩	⟨0.951⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨0.859⟩
Order 14	-0.009	0.052	-0.042	0.752	0.483	0.008	-0.040	0.015	-0.005
	(0.036)	(0.030)	(0.042)	(0.429)	(0.414)	(0.033)	(0.039)	(0.034)	(0.005)
	[0.796]	[0.086]	[0.316]	[0.080]	[0.244]	[0.812]	[0.309]	[0.657]	[0.321]
	⟨1.000⟩	⟨0.922⟩	⟨1.000⟩	⟨0.907⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩
Order 15	-0.012	0.054	-0.043	0.944	0.629	0.007	-0.050	0.016	-0.004
	(0.037)	(0.031)	(0.043)	(0.435)	(0.422)	(0.034)	(0.040)	(0.034)	(0.005)
	[0.751]	[0.079]	[0.316]	[0.030]	[0.136]	[0.847]	[0.210]	[0.644]	[0.418]
	⟨1.000⟩	⟨0.902⟩	⟨1.000⟩	⟨0.714⟩	⟨0.979⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩
Order 16	-0.004	0.049	-0.045	1.130	0.799	0.011	-0.043	0.016	-0.003
	(0.038)	(0.029)	(0.043)	(0.450)	(0.438)	(0.034)	(0.040)	(0.034)	(0.006)
	[0.919]	[0.095]	[0.293]	[0.012]	[0.068]	[0.744]	[0.276]	[0.644]	[0.633]
	⟨1.000⟩	⟨0.934⟩	⟨1.000⟩	⟨0.592⟩	⟨0.868⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩
Order 17	-0.016	0.029	-0.013	1.270	0.967	0.026	-0.040	0.031	-0.003
	(0.038)	(0.027)	(0.042)	(0.459)	(0.442)	(0.032)	(0.040)	(0.033)	(0.006)
	[0.674]	[0.274]	[0.749]	[0.006]	[0.029]	[0.416]	[0.325]	[0.341]	[0.640]
	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨0.528⟩	⟨0.710⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩
Order 18	-0.023	0.021	0.002	1.429	1.072	0.029	-0.037	0.026	0.000
	(0.037)	(0.026)	(0.042)	(0.471)	(0.444)	(0.034)	(0.041)	(0.035)	(0.007)
	[0.545]	[0.427]	[0.963]	[0.002]	[0.016]	[0.402]	[0.375]	[0.446]	[0.960]
	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨0.476⟩	⟨0.625⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩
Order 19	-0.021	0.032	-0.012	1.103	0.975	0.019	-0.032	0.004	0.002
	(0.041)	(0.032)	(0.047)	(0.489)	(0.446)	(0.039)	(0.044)	(0.040)	(0.009)
	[0.612]	[0.303]	[0.806]	[0.024]	[0.029]	[0.624]	[0.473]	[0.918]	[0.781]
	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨0.690⟩	⟨0.711⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩
Order 20	0.002	0.064	-0.067	0.433	0.650	-0.005	-0.018	-0.030	-0.004
	(0.051)	(0.047)	(0.059)	(0.533)	(0.492)	(0.052)	(0.051)	(0.052)	(0.007)
	[0.965]	[0.168]	[0.259]	[0.416]	[0.186]	[0.922]	[0.722]	[0.560]	[0.555]
	⟨1.000⟩	⟨0.991⟩	⟨1.000⟩	⟨1.000⟩	⟨0.998⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩	⟨1.000⟩
Order 1 Mean	0.199	0.081	0.720	38.217	37.762	0.815	0.619	0.775	0.016
Observations	325,731	325,731	325,731	353,151	353,151	352,443	352,443	352,443	353,151

Notes: Each column reports coefficients from OLS regression of the covariate on order indicators (Order 1 omitted). Standard errors in parentheses, uncorrected p-values in brackets, Romano-Wolf corrected p-values in angle brackets. Standard errors clustered by family ID.

Table B.5: Characterizing those affected by order effects

	All		Non-White mothers		White mothers	
	All	Compliers	All	Compliers	All	Compliers
Baby's age	-114.274	-32.310	-103.665	-72.691	-124.500	-6.134
	(0.913)	(24.626)	(1.342)	(37.339)	(1.229)	(38.840)
White mother	0.510	0.569				
	(0.004)	(0.147)				
Black mother	0.253	0.187	0.517	0.429		
	(0.004)	(0.123)	(0.006)	(0.240)		
Mother's age'	26.050	29.158	25.229	32.726	26.837	26.774
	(0.065)	(1.875)	(0.087)	(4.000)	(0.094)	(2.332)
Trigger state	0.288	0.287	0.279	0.320	0.296	0.268
	(0.004)	(0.144)	(0.006)	(0.220)	(0.006)	(0.191)
Post Dobbs	0.220	-0.085	0.257	-0.156	0.184	-0.035
	(0.004)	(0.107)	(0.006)	(0.205)	(0.005)	(0.118)
Trigger state & Post Dobbs	0.061	-0.118	0.067	-0.192	0.056	-0.065
	(0.002)	(0.086)	(0.003)	(0.163)	(0.003)	(0.098)
Budget	43,563.220	37,710.428	43,995.978	38,298.506	43,146.128	37,316.255
	(397.771)	(1,968.132)	(578.437)	(3,119.858)	(297.777)	(2,517.000)
AP Salary	182,005.193	171,239.857	181,386.303	179,845.560	182,600.086	167,357.199
	(3,611.925)	(31,808.239)	(4,604.106)	(49,741.687)	(3,456.104)	(40,726.351)

Notes: The table considers the pair mother-adoptive family as the unit of analysis. The number of mothers is 6,685 for White mothers and 6,451 for Non-White mothers. The treatment (Z) is to appear in order 1-10, and not treated is to appear in order 11-20. Treatment status (D) equals 1 if a match occurs and 0 if not. To identify characteristics of complier birth mothers, we estimate the effect of D on $X \times D$ using Z as an instrument where X is a mother's characteristic. Regressions are run separately for each X, and errors are clustered at the mother level. The regressions only include mothers whose children's age is below 300 days. Characteristics of adoptive families, i.e. Budget, AP Salary, are treated similarly with the exception that errors are cluster at the adoptive family level.

C Qualitative Analysis

We conduct a qualitative analysis to serve as supplemental evidence to our primary quantitative findings. This analysis examines what birth mothers state as deciding factors when discussing their search for adoptive parents. We examine a public blog to measure what birth mothers may be considering when searching for adoptive families. The public blog allows us to observe the decision process of birth mothers who may not conventionally select an adoption organization similar to our partner.

The analysis is conducted on a sample of data extracted from a large public online blog centered on discussing adoption related topics.[5] The site is comprised of approximately 85,000 unique users who discuss various adoption related topics on numerous forums. We use a sample of the blog comprising 25,940 unique user posts.[6] Each user has their post history tested against a set of three criteria that determines whether the user has made relevant statements with respect to the research focus of our paper.[7] Of the total unique users, 452 are identified to have made posts that satisfy criteria classifying them as a birth mother who has placed her child for adoption and has discussed her reasoning for selecting an adoptive family.

To analyze the public forum data, we use ChatGPT, an advanced Artificial Intelligence (AI) based on large language model (LLM) technology, to test whether each post of a user passes or fails against the three criteria to determine if the user is relevant to our question After a user is determined to meet the stated criteria, the LLM creates a "*general bucket*" term to classify the nature of the post. The *general bucket* term is used to classify the written reasons as to what matters for a birth mother in selecting an adoptive family. The LLM created 1,120 *general buckets*, 180 of which are unique, to synthesize the reasons why birth mothers selected certain adoptive families.[8] To conduct the analysis, we manually combine

[5] The data is from adoptions.com

[6] Due to financial constraints we do not run the analysis on the total population.

[7] The specific instructions and process is described in detail in the "Qualitative Analysis README."

[8] A birth mother may have listed multiple reasons to why a particular adoptive family was selected or may have mentioned different reasons across posts. The LLM would produce multiple *general bucket* terms

the number of *general bucket* terms to 13 final classifications which we call "*categories*."[9] *Categories* encompass the full set of different motivations for a birth mother to select an adoptive family. The *categories* that were chosen are the following: Adoption Conditions, Age and Health, Culture and Religion, Education and Occupation, Emotion and Feeling, Family Dynamics, Financial, Order Viewed, Parenting Skills and Value, Race, Siblings, Timing, and Other.

Categories are chosen to reduce the number of *general buckets* into a reasonably digestible quantity without losing the essence of the original post. These *categories* are chosen based on a general classification of the *general bucket*. Classifications encompass the key dimensions we expect matter in the selection of an adoptive family. The initial framework for the LLM instruction is based on adoption practitioner knowledge and a variety of adoption-related interviews, then iteratively refined through manual categorization based on the LLM's classification patterns. We approach categorization from an exploratory perspective. These practical classifications fall into five broad factor groups: economic factors (Financial; Education and Occupation), emotional factors (Emotion and Feeling; Parenting Skills and Values), demographic factors (Age and Health; Family Dynamics; Siblings), cultural factors (Culture and Religion; Race), and system factors (Adoption Conditions; Order Viewed; Timing). The "Other" *category* serves as a catch-all for any posts not fitting into a particular classification. These different *categories* are not mutually exclusive, and the majority of birth mothers cite multiple categories as reason of selecting a particular adoptive family. Rather, the intent of this classification is to serve to capture a complete picture of adoptive family selection reasons.

Each *category* is defined as follows, organized by factor group: Financial accounts for the factors that directly relate to economic position of the adoptive family. Education and Occupation accounts for values relating to how the adoptive family creates economic

per user if applicable.

[9]This initial analysis of synthesizing to *categories* was conducted by only examining the output of *general bucket* terms from the LLM.

stability in the household. This presents as noting occupational fields a particular member of the adoptive family is in. Emotion and Feeling captures the intangible factors that relate to selecting an adoptive family. Parenting Skills and Values reference the choice of adoptive family based on a particular ability or belief. Age and Health captures reasons relating to the the age and/or health of either the adoptive family or baby. Typically, this is relating the age of the birth mother to the adoptive family. Family Dynamics relates to the circumstances or make-up of a particular adoptive family. Birth mothers state common reasons such as having a prior relationship with the family, or their preference toward adoption in their family formation decisions. Siblings captures the potential siblings of the baby. We note that the stated reasons often are capturing the existence of another sibling that the baby would join.

Culture and Religion captures factors based on the birth mother's preferences around their faith or upbringing. We find that this mostly relates to specifying a particular faith or belief-system birth mothers value in an adoptive family. Race relates to denoting the racial composition of the adoptive family. This is shown by noting what the racial composition the adoptive family is in relation to the baby. Adoption Conditions measure reasons relating to the terms of the adoption. These are often involving the "openness" of the adoption with respect to visitation and communication between the adoptive family and birth mother. Order Viewed was intentionally prompted as it relates to our primary quantitative findings. Birth mothers note the relative position or design of the adoptive profile viewed when searching. Lastly, Timing captures reasons relating to the adoptive family position in the adoption system during the birth mother's search process. These reasons are often capturing the "right moment" feelings that factor into the selection decision.

Classifying a user's discussion to a few simple terms may obfuscate the original intention of the post. To account for this possibility, we had the LLM identify a "*specific bucket*" within each *general bucket* where appropriate. *Specific buckets* are utilized to provide context to classifications, particularly in understanding the direction of preference of a *category* (ex.

distinguishing older versus younger when referring to the age of the adoptive family as a reason for selection). 85 of the 452 users were classified as having a *specific bucket* within a *general bucket* classification resulting in 165 *specific buckets* a subset of the total frequency of *categories* observed. Similar to the prior analysis, each *specific bucket* is manually classified within every *category* to best simplify the frequency of the stated motives of birth mothers. The classification of *specific buckets* are referred to as "specific reasons."

The results of the public blog data analysis is shown on Table C.1. The *categories*, listed in bold within the classification column, displays the total number of users having their posts be classified as selecting an adoptive family for that purpose, as well as, the relative percent of users having that *category* selected. Additionally, under each *category* within the classification column, the *specific bucket* shows the proportion of users with additional context to their *category* assignment. If users were not assigned to a *specific bucket*, then they fall into the"no specific reason" subclassification. Table C.2 shows the analysis of translating the LLM's *general bucket* terms to *category* terms.[10] The manual classification of each *specific bucket* reason from the original *specific bucket* term is shown in Table C.3.[11]

We find that birth mother's most common stated reason for selecting an adoptive family is based on the Siblings category. 29% of reasons for selecting an adoptive family has to do with the potential siblings the baby of the birth mother would have. The next common *category* is Timing at 19% of posts. Birth mothers indicate that the selection of a particular adoptive family is in large part due to the introduction or speed of the process with that family. The final most common *category* is Culture and Religion at 13%. Birth mothers denote that the background of the adoptive family as an important factor in their selection process.

[10]The LLM's *general bucket* classification results are left mostly in their original output. We manually redefined 8 nonsensical *general bucket* terms based on reanalyzing the user's original posts to properly represent the intention of the original post and subsequent *category* classification.

[11]Initially, the LLM coded 166 total *specific reasons* to contextualize birth mother posts. 24 of the 166 total posts were manually reclassified by changing the initial *general bucket* within a *category* to a better fitting *category* based on the *bucket* term and *specific bucket* combination, resulting in a more appropriate classification (these general bucket terms are denoted with an * in Table C.2). 1 *specific bucket* was manually removed as it is uninterpretable.

We acknowledge potentially important limitations that should be considered when interpreting these results. Using an AI system to generate initial categorizations is necessary for processing the size of information we analyzed, but can overlook or misclassify information that would be caught by a human researcher. To reduce potential error, we manually examine the every outputted *general bucket* and *specific bucket* terms and flag any terms that seems peculiar. We then review the raw posts associated with that classification We anticipate that the most common errors are going to result from the LLM classifying non-birth mothers speaking about the adoption experience from the perspective of a birth mother or birth mothers speaking about non-domestic private adoptions. We feel that the specific directions for the LLM filters for these cases as carefully as it can. Next, *categories* are created based on researcher discretion, which can lead to ex-post classifications that best suit a particular narrative inconsistent with the underlying findings. We present the information relating to the classifications in Tables C.2 and C.3. Readers are encouraged to reassign classifications if they feel the assignment was incorrectly made and reexamine the primary findings. Lastly, we analyze a large scale of data but at the cost of precision. We boil down a significant process into several final classifications that can miss the nuance of this process. We believe that the design of the *categories* captures a robust set of factors based on the individual reasons captured through our analysis. Importantly, we allow for posts to fit into more than one *category* to allow for a multi-faceted approach to selecting a particular adoptive family.

Table C.1: Qualitative Analysis of Adoption Blog

Classification	Frequency	Percent
Adoption Conditions	**29**	**3%**
Frequent Contact	1	
Name Agreement for Child	2	
Open Adoption	3	
No Specific Reason Given	23	
Age and Health	**67**	**6%**
Experience with Child's Health Issues	1	
Older than Self	23	
Similar Age	1	

Table C.1 – continued from previous page

Classification	Frequency	Percent
Younger than Self	1	
No Specific Reason Given	41	
Culture and Religion	**1340**	**13%**
Catholic	4	
Christian	9	
Hawaiian	1	
Irish	1	
Jewish	1	
Latter-Day-Saints	3	
Shared Faith	3	
No Specific Reason Given	118	
Education and Occupation	**41**	**4%**
Child Care Provider	1	
Communications Technician	1	
Computer Programmer	1	
Non-Profit	1	
Nurse/Doctor	5	
Police Officer	1	
Retired	1	
Stable Career	1	
Stay-at-Home Mom	1	
No Specific Reason Given	28	
Emotion and Feeling	**51**	**5%**
Controlling/Manipulative	1	
Emotional/Personal Connection	5	
No Specific Reason Given	45	
Family Dynamics	**58**	**5%**
Adopt Sibling Group	8	
Adopted Parent	1	
Approve Family Preferences	2	
Have Pets	1	
Preference to Adopt First	1	
Preferred Infant	1	
Related to Family	3	
Relationship with Family	3	
Supportive Home	4	
Two-Parent Household	1	
Young/Single Birth Mother	1	
No Specific Reason Given	32	

Table C.1 – continued from previous page

Classification	Frequency	Percent
Financial	**22**	**2%**
Financially Stable	1	
Not Wealthy	1	
Wealthy	1	
No Specific Reason Given	19	
Order Viewed	**88**	**8%**
Colorful Profile	1	
Referred Profile	1	
Shown Early	1	
Shown Late	1	
No Specific Reason Given	84	
Parenting Skills and Values	**34**	**3%**
Accepting of Special Needs Child	1	
Prior Parental Experience	1	
No Specific Reason Given	32	
Race	**47**	**4%**
Bi-Racial	2	
Black	1	
German	1	
Haitian	1	
Hispanic	1	
White/Native American	1	
No Specific Reason Given	40	
Siblings	**320**	**29%**
Existing Relationship with Sibling	1	
Have Adopted Child (1)	2	
Have Adopted Children (1+)	3	
Have Bi-Racial Siblings	1	
Have Child (1)	4	
Have Children (1+)	11	
Have Female/Male Child	5	
Have Nieces/Nephews	1	
No Children	1	
No Specific Reason Given	291	
Timing	**210**	**19%**
Emotional Readiness	1	
Fast Process	5	

Table C.1 – continued from previous page

Classification	Frequency	Percent
Father Left	2	
Matched during Pregnancy	2	
Right Family	1	
Right Moment	8	
Slow Process	1	
No Specific Reason Given	190	
Other	**11**	**1%**
No Specific Reason Given	11	
Total:	1,120	

Table C.2: Qualitative Analysis Categories and General Bucket Terms

Category	LLM General Bucket
Adoption Conditions	Adoption Conditions, Adoption Experience, Approach to Open Adoption, Communication, Communication with First Mom, Communication with Foster Mom, Contact frequency, Contact with birth mother, Ensuring Child Knows Her Origins and Extended Family, Family Involvement, Inadequate self-education on open adoption, Open Adoption Arrangement, Open adoption preference, Open Adoption Relationship, Open Adoption Views, Open Adoption with Bio Mom, Philosophy on open adoption, Potential for Open Adoption, Promise to Maintain Birth Family Connections, Protection of Anonymity, Quick decision-making process, Relationship with Birth Mother, Relationship-building, Shared Connection, Siblings*, Support during birth and post-birth recovery, willing to keep the name given by the birth mother
Age and Health	Age, Challenges, Health and longevity, Medical History, Medical Similarity, Wellness
Culture and Religion	Community involvement, Connection to Child's History/Biology, Cultural Diversity, Culture/Heritage, Faith in God, Morals, Religion, Religious Belief, Timing*, Tribal Representatives' Support
Education and Occupation	Drug Counselor Influence, Education, Education of adoptive parents, Occupation

Table C.2 – continued from previous page

Category	LLM General Bucket
Emotion and Feeling	Ability to handle physical and emotional needs, Apperance, appreciation of the chance to parent, attitude towards birth parents, Compassion, Desire to be parents, destined to be his parents, envisioning happiness, Emotion, emotional connection, Emotional Stability, Emotional Support, Feeling of peace, Honesty, Honesty in asnwering questions, lack of coercion, Laughter and Humor, Leap of faith, Love, Love and Attachment Shown to Child, Love and Security, loving environment with two parents, Openness, Patience and understanding, personal connection and dedication to the child's well-being, personal conviction, personal support, Personal Traits, Personality, Physically and Emotionally can Handle it, Promise of a Good Life, Relationship, Relationship dynamic, Religion*, Respect, Respite availability, Shared personality traits, Transition Handling, Trust, trust in adoptive parents' character and parenting, Uncommon shared middle name with birth mother, Understanding, understanding of birth mother's situation
Family Dynamics	Acceptance by Family Members, Emotional Support Structure, Extended Family, Extended family involvement, Familial Connection, Family Closeness, Family Dynamics, Family Integration, Family Structure, Family Support, Lack of family support, Living Situation, no criminal backgrounds, Order of Presentation*, Other children from previous adoption experiences, other family members adopted previous siblings, Personal Experience and Similarities with Birth Family, Personal Experience in Adoption, Previous Relationships, Real Family Life, Relationship*, sense of family integration, Siblings*, solid marriages, Stability, Stability and Calm, Strong extended family, Support, Support Network, Support system, Support System Availability, Timing*, Two-parent Family, Two-parent home, Two-parent household, unpleasant situation with the father of her other daughters, wants a big family
Financial	Better Life, Desire to provide better life, Financial Display, Financial preparedness, Financial Security, Financial Stability, Financial Stability/Salary, Financially, Opportunities, Provide well for my son, Salary, Wanted more for the child than the birth mother could provide, Wanted more for the child than the birth mother could provide, wanting her child to have more than she could provide
Order Viewed	Order of Presentation

Table C.2 – continued from previous page

Category	LLM General Bucket
Parenting Skills and Values	Behavior Management, Breastfeeding Intentions, Commitment to Raising the Child with Wisdom and Compassion, Concern for birth child's postpartum period, Creativity, Dedication to Child's Needs, Discipline, Experience, Future experiences for the child, Guidance, Health Concerns, Health needs of the child, health of child, Health/Ability to Parent, Inability to handle adopted child's special needs, Interests, Lifestyle, Mental Health Issues, Safety Concerns, Political views, Safety/Environment Concerns, Sensory Processing Disorder Knowledge, Shared Values, Shared Values/Beliefs, Special Needs, Supportive of her needs, Thoughts on child-rearing, Values, Vegetarian Lifestyle
Race	Acceptance of Transracial Families, Physical likeness, Race
Siblings	Age*, Siblings
Timing	Timing, timing of decision
Other	Attachment Issues, Attachment to Foster Mother, Fear for adopted child's well-being without adoption, Foster Care System Familiarity, Proximity, Proximity of Birth Mother Previous Foster Family Treatment, Previous Fostering Experience, Suburbia, Travel Options

Table C.3: Qualitative Analysis Specific Bucket Terms and Specific Reasons

Category	LLM Specific Bucket	Specific Reason
Adoption Conditions	honor names from both families.	Name Agreement for Child
	maintained open communication.	Open Adoption
	Once a week	Frequent Contact
	Open adoption	Open Adoption
	similar naming desires	Name Agreement for Child
	wants to maintain relationship with kids	Open Adoption
Age and Health	older	Older Than Self
	older	Older Than Self
	older	Older Than Self
	older and more stable than self	Older Than Self
	older than self	Older Than Self
	older than self	Older Than Self
	older than self	Older Than Self
	older than self	Older Than Self
	older than self	Older Than Self
	older than self	Older Than Self

Table C.3 – continued from previous page

Category	LLM Specific Bucket	Specific Reason
	older than self	Older Than Self
	older than self	Older Than Self
	older than self	Older Than Self
	older than self	Older Than Self
	older than self	Older Than Self
	older than self	Older Than Self
	older than self	Older Than Self
	older than self	Older Than Self
	older than self	Older Than Self
	older than self	Older Than Self
	older than self	Older Than Self
	older than self	Older Than Self
	older than self	Older Than Self
	Prepared for child with health issues (heart defect).	Experience with Health Issues
	similar to herself	Similar Age
	younger than self	Younger Than Self
Culture and Religion	Catholic	Catholic
	Catholic	Catholic
	Catholic	Catholic
	Catholic	Catholic
	Celtic name for Irish heritage	Irish
	christian family	Christian
	desires to raise child with priesthood	Christian
	felt guided by God	Christian
	found through church	Christian
	God's plan	Christian
	God's plan.	Christian
	Godly home	Christian
	good morals/values suggested by LDS faith	Latter-Day-Saints
	involved in spiritual community	Shared Faith
	LDS (Latter-day Saints)	Latter-Day-Saints
	LDS family	Latter-Day-Saints
	maintain cultural ties with Hawaiian heritage	Hawaiian
	man and woman in a traditional union	Shared Faith
	of the same faith as the birth mother	Shared Faith
	prayer and God mentioned	Christian
	respecting her wishes for baptism	Christian

Table C.3 – continued from previous page

Category	LLM Specific Bucket	Specific Reason
	specifically wanting Jewish parents	Jewish
Education and Occupation	both nurses	Nurse/Doctor
	communications technician	Communications Technician
	husband is a computer programmer	Computer Programmer
	husband took early retirement	Retired
	licensed home childcare provider	Child Care Provider
	nurse	Nurse/Doctor
	nurse/counselor	Nurse/Doctor
	nurses	Nurse/Doctor
	pediatrician and R.N.	Nurse/Doctor
	police officer	Police Officer
	stable jobs for 5 years	Stable Career
	stay at home mom.	Stay-at-Home Mom
	works in the non-profit world	Non-Profit
Emotion and Feeling	emotional and personal connections	Emotional/Personal Connection
	emotional connection and support during birth.	Emotional/Personal Connection
	feels new family is controlling and manipulative	Controlling/Manipulative
	happy and well-adjusted	Emotional/Personal Connection
	holds a special place in her heart	Emotional/Personal Connection
	Sincerity/ being themselves	Emotional/Personal Connection
Family Dynamics	abiding document of intention for both partners to be present in the child's life	Two-Parent Household
	baby will have a sibling through previous adoption with same parents	Adopt Sibling Group
	because they are family	Supportive Home
	could not provide a stable home due to being a teenager and home life situations.	Young/Single Birth Mother
	developed a good friendship with the adoptive parents.	Relationship with Family
	did not want to adopt a child older than the duration of their marriage	Approve Family Preference
	distant family through marriage	Related to Family
	existing daughter who is biologically related (DD is bio)	Adopt Sibling Group
	family and church support	Supportive Home

Table C.3 – continued from previous page

Category	LLM Specific Bucket	Specific Reason
	had a positive relationship with father's family before marriage.	Relationship with Family
	have a shepherd dog friendly to children	Have Pets
	interfamily dynamic with sister as adoptive mother	Related to Family
	keeping biological siblings together	Adopt Sibling Group
	keeping siblings together/stability	Adopt Sibling Group
	knew the adoptive parents very well	Relationship with Family
	mother had been adopted herself	Adopted Parent
	preferred an infant and were aware of age considerations in domestic adoption.	Preferred Infant
	received unexpected support from friends and family.	Supportive Home
	second cousin by marriage	Related to Family
	some family are just getting used to the idea of 1	Approve Family Preference
	stable home and relationship	Supportive Home
	wanted to adopt before trying to get pregnant	Preference to Adopt First
	wanted to keep siblings together	Adopt Sibling Group
	wanting to keep sibling group together	Adopt Sibling Group
	wants to keep siblings together	Adopt Sibling Group
	willing to take a sibling group	Adopt Sibling Group
Financial	can make it work	Financially Stable
	despite not making a lot of money	Not Wealthy
	very well off	Wealthy
Order Viewed	part of final choices	Shown Late
	profile shown before homestudy completed	Shown Early
	received call about adoption referral after husband woke up with a stomach bug	Referred Profile
	stood out because it was colorful	Colorful Profile
Parenting Skills and Value	previous parenting experience	Prior Parental Experience
	willing to care for children with special needs.	Accepting of Special Needs Child
Race	biracial preference	Bi-Racial
	black (Haitian/not African American)	Haitiian

Table C.3 – continued from previous page

Category	LLM Specific Bucket	Specific Reason
	Caucasian or Native American ethnicity preference.	White/Native American
	children are black	Black
	German	German
	Hispanic	Hispanic
	mixed race	Bi-Racial
Siblings	already had a natural child	Have Child (1)
	already had an adopted daughter	Have Adopted Child (1)
	already has a girl an wants one of each.	Have Female/Male Child
	amom already had two children and went on to adopt another.	Have Children (1+)
	child already having a relationship with the adoptive father's son	Existing Relationship with Sibling
	considering a sibling set with a toddler and a baby in the future but started with a baby.	Have Child (1)
	had a daughter	Have Female/Male Child
	has children already	Have Children (1+)
	has siblings	Have Children (1+)
	have children	Have Children (1+)
	little boy to play with her nephew	Have Female/Male Child
	older child who would be the big sister to her daughter.	Have Female/Male Child
	other kids be adopted as well.	Have Adopted Children (1+)
	other kids be adopted as well.	Have Adopted Children (1+)
	part of a sibling group	Have Children (1+)
	play time with nieces/nephews	Have Nieces/Nephews
	presence of other children in adoptive family	Have Children (1+)
	providing a sibling for the child	Have Child (1)
	reference to in-laws being biracial and having a multiracial family.	Have Bi-Racial Siblings
	the adoptive mother is an only child nearby	No Children
	The adoptive parents had previously adopted.	Have Adopted Child (1)
	toddlers from foster care	Have Adopted Children (1+)
	twin girls	Have Children (1+)
	under 2	Have Children (1+)
	wanted a girl to bond with as she has with her mother	Have Female/Male Child

Table C.3 – continued from previous page

Category	LLM Specific Bucket	Specific Reason
	wanted the child to have siblings	Have Children (1+)
	wanted the child to have siblings.	Have Children (1+)
	will have a sibling	Have Child (1)
	younger than the current children.	Have Children (1+)
Timing	'the second I read it (after reviewing close to 50) I knew they were 'the ones'	Right Moment
	after raising 5 adult children and having grandchildren	Right Moment
	biofather not actively involved.	Father Left
	chose to wait to find the right person to marry and start a family	Right Moment
	during process of adoption mentioned multiple periods of waiting	Right Moment
	emotional readiness	Emotional Readiness
	fast process	Fast Process
	fast process	Fast Process
	felt child was meant for them	Right Family
	fitting into family plans after school and marriage.	Right Moment
	less than a year wait	Fast Process
	Matched and shower thrown once	Matched during Pregnancy
	Matched around 5 months pregnant	Matched during Pregnancy
	needed someone to be nice at the time.	Right Moment
	opportunity arose shortly after beginning the adoption process.	Fast Process
	process went quickly	Fast Process
	spent a lot of time with adoptive parents before birth	Right Moment
	start the new year as a family officially	Right Moment
	the father had left	Father Left
	the situation came up right in Idaho	Right Moment
	waiting over a year	Slow Process

D Qualitative Analysis README

Link to code: https://github.com/fwromano/AdoptionSentimentAnalysis

The data source was scraped from online forums. The data was presented in the form of a pickled Python object. For the text classification, OpenAI's best model at the time, "gpt-4-1106-preview" (commonly known as GPT-4 Turbo), was accessed via an API and passed the first 50,000 characters of each user's content. This limit was chosen due to the model's context window, which determines how much it can recall from the conversation. Furthermore, this limit only impacted a small number of the sampled users since the average length of a user's written content was 15,000 characters. The first dataset was processed in a simple format, associating each post with a user. This was restructured so that all the content written by one user was grouped together. The next step was to parse the information from the text via the API with the following system prompt: [1]. After the raw data had been interpreted, it was sorted along the search parameters and generated reasons. The second dataset was already in a one-to-one format of users to posts, so the preprocessing step could be skipped. There were considerations on the use of acronyms in the data and the model's ability to interpret them. An experiment was conducted with two prompts: one with all the acronyms and their meanings, and one without. The results suggested that doubling the system prompt's length due to the acronym table resulted in a diluted understanding of the object model, causing certain cases of interest to be skipped.

The next experiment included more categories and reduced the size of the acronym table to mitigate prompt dilution. The results indicated that the new categories were useful, but the acronyms again had no effect. The final decision was to include the new categories and preprocess some acronyms to be replaced with their actual meaning (e.g., "BM" was replaced with "Birth mother"). The revised prompt [2] was then run on the preprocessed and cleaned data. The data was parsed and organized based on the generated categories.

[1] System prompt from the 1st data run: "You are an Adoption Agent who specializes in reviewing and understanding online posts relating to adoptions. Given the post, only

respond yes or no to each of the first three questions: 1) Is the author a birth mother? 2) Has the birth mother actually given up a child for adoption? 3) Did the birth mother give a reason why she chose the adoption family? Finally, if the answer to the first three questions were all yes, then respond concisely to 4) What are the main and specific reasons the adoption family was chosen, if any? Choose all that apply: Salary, Age, Occupation, Race, Religion, Order of Presentation, Timing, Siblings, etc., or N/A. Example response: 1) yes 2) yes 3) yes 4) Age: older than self" [2] System prompt from the 2nd data run: "You are an Adoption Agent who specializes in summarizing feedback notes from birth mothers examining a specific adoptive family profile. For the given note, concisely answer: What are the birth mother's main observations about the adoptive family? Respond with one or more of the following example reasons: Adoption Conditions, Age and Health, Culture and Religion, Education and Occupation, Emotion and Feeling, Family Dynamics, Financial, Other, Order Viewed, Parenting Skills and Values, Race, Siblings, Timing, N/A. Response structure should be like this example: Culture and Religion: Catholic, Siblings: two sisters"

E Extended Search Model

We extend the model of search by including potential supply changes in the adoption market. We introduce a variable p_k that captures the ability to search for adoptive families in period k.

The model addresses two features of the search process: (1) how intensely to search for an adoptive family and (2) whether to choose an adoptive family from those available. We assume the search occurs over discrete periods like weeks, months, or trimesters. Given its significance, we consider the birth period to be 0, and k represents periods since birth. A negative k is equivalent to time before birth. We denote by p_k the probability that a mother would be able to place a child in adoption in period k or after and assume that $p_k \geq p_{k+1}$. This captures the fact that the mother's options worsen as the child gets older. For instance, if we set k to represent trimesters and $p_k = 1$ for $k \leq 1$ and $p_k = 0$ otherwise, we have a search model with a deadline where no adoptions are possible after the baby's first trimester after birth. A mother exercises her outside option once $p_k = 0$. Variable p_k allows us to measure the effect of a deadline change (see Landsberger and Peled, 1977).[12] R_k represents the outside option to placing the child for adoption. The outside option includes the possibility of having an abortion, which is associated with lifetime utility A, and the possibility of raising the child, which is associated with lifetime utility H. We let R_k depend on the period k since the option set changes as the option of abortion disappears over time.

We distinguish changes in the probability of being able to access an adoption, p_k, and changes in the outside options available to the mother, R_k, i.e. having an abortion or keeping the child. R_k can be affected by government transfers to families with children or reproductive policies. p_k captures factors affecting the demand for adoptive children, such as age of the child or laws limiting adoptions. We, therefore, consider R_k to represent conditions more or less conducive to raising a child and the possibility of terminating a pregnancy. This

[12] Landsberger and Peled (1977) introduce variable p_k in a model of search to represent varying supply conditions faced by buyers.

means that deadline effects might be due to changes in the conditions for adoption (lower demand for older children or a drop in p_k) and changes in the feasibility of abortions or conditions for keeping the child (or changes in R_k). The model can accommodate the case where mothers consider only adoptions or abortions by making $p_k = 0$ for k passed the limit for a legal abortion, i.e., an abortion occurs if a suitable adoptive family is not found by a deadline.

In a period in which a mother can place a child for adoption, she decides how intensely to search for an adoptive family. The intensity of the search in period k is denoted as s_k, where $s_k \in [0, 1]$. The intensity of the search, s_k, determines the probability of finding a conditionally acceptable adoptive family.[13] This family is the best among those inspected, and the mother attributes a lifetime utility equal to u_k. In our setting, accepting a family for adoption carries a monetary transfer M_k that depends on the baby's age. These transfers are typically used to cover the costs incurred during pregnancy. We do not model this variable explicitly, i.e., we assume $\forall k, M_k = 0$, because we do not have complete information on transfers and it does not significantly alter the hypotheses of the model we want to test.

The distribution of the best option is $F_k = F$, which we assume is stationary over the relevant time in which the mother makes her decision.[14] We observe the characteristics of the adoptive families on our partner's website, but we do not observe the alternatives the mothers observes. A mother incurs cost $-c(s_k)$ if she wants to find a family with probability s_k. We assume that the cost function is increasing, strictly convex, and equals 0 if search is not pursued. If the observed utility is u_k, the mother chooses the family or waits until the next period to decide. We denote the expected utility, conditional on being able to search, of waiting until the next period by v_{k+1}. If the search produces no adoptive family (which occurs with probability $(1 - s_k)$), the mother waits. We assume that search intensity does

[13] We normalize search intensity to represent the probability that at least one adoptive family is found. See Le Barbanchon et al. (2024) for a discussion of this model in the labor literature.

[14] Over 300 adoptive families are added to the site each year, roughly equivalent to the number of adoptions placed each year. Around 3,000 different mothers visit the agency's website each year.

not affect the distribution of alternatives.[15] We denote $p = \{p_k\}_k$ and $R_k = max\{A, H\}$ if A is available and $R_k = H$ if not. We let R denote the vector of values of R_k affecting mothers' decisions. We note that in our model, mothers search for adoptive families for as long as possible if no suitable family is found. Mothers exercise the outside option, i.e. abortion or raising the child themselves, only when no more search is possible. We consider this a reasonable assumption given the revealed interest in the possibility of adoption of the mothers in our study.

Search intensity s_k can be interpreted as a rescaling of arrival times within a period if the probability of finding an adoptive family monotonically increases in arrival time and the cost function is the cost associated with arrival time. Our current presentation simplifies the algebra significantly and helps relate our approach to previous literature on job search (Card et al., 2007; Chetty, 2009).

We determine the expected utility conditional on being able to search in period k as follows:

$$\begin{aligned} v_k(R,p) = -c(s_k) + s_k E[max\{u_k, p_{k+1}v_{k+1}(R,p) + (1-p_{k+1})R_{k+1}\}] \\ +(1-s_k)(p_{k+1}v_{k+1}(R,p) + (1-p_{k+1})R_{k+1}) \end{aligned}$$

The dependency of v_k on k is handled using subscripts, and we avoid cluttering the notation by not using subscripts for R_k and p_k. Expected utility is a function of search cost c_k in period k and the weighted average of flow utility when search is successful and unsuccessful. We denote the ex-ante value function, i.e. before learning if search can take place by $J_k(R,p) = p_k v_k(R,p) + (1-p_k)R_k$. We can rewrite the original problem as:

[15] This assumption simplifies the analysis since allowing the distribution of the best option to depend on the intensity of the search would complicate the algebra without adding much economic insight.

$$v_k(R,p) = -c(s_k) + s_k \int_{J_{k+1}(R,p)}^{\infty} (u_k - J_{k+1}(R,p))dF(u) + J_{k+1}(R,p) \tag{7}$$

$$= -c(s_k) + s_k Q(J_{k+1}(R,p)) + J_{k+1}(R,p), \tag{8}$$

where $Q(J_{k+1}(R,p))$ is the *average* gain from an adoption on searching at time k. Note that $\partial Q(x)/\partial x \leq 0$, i.e. as the outside option, R, gets better or the ability to continue searching, p_k, increases, the gain for searching for adoptive parents declines (i.e., people are more likely to put off searching).[16] The continuation valuation of search declines with K, i.e. as the deadline approaches.[17] This implies that the probability of adoption, i.e., the willingness to accept worse matches, increases as the deadline approaches. Note that the outside option, R_k, weakly worsens if the option of an abortion is no longer available. This means that search intensity should increase in anticipation of such an option being removed, and the probability of adoption conditional on search should also increase if such an option is removed. Similarly, a model where k represents trimesters and $p_k = 0$ for $k \geq 1$ and $p_k = 1$ otherwise would predict that search intensity will increase as birth approaches. The same pattern is expected for the probability of adoption. Mothers will be more willing to follow through with an adoption the older the child. If we let $p_k = 0$ for $k \geq -1$ and $p_k = 1$ otherwise, we obtain similar patterns for those considering abortions before the third trimester.

The dependence of $v_k(R_k, p)$ on the outside option speaks to selection issues in the adoption market. Mothers with relatively lower R's should enter the market earlier, search more intensely, and be more likely to place the child for adoption to a given family. Strong enough selection effects can produce results contrary to a finite horizon search model. It is an empirical question whether deadline or selection effects dominate this market.

[16] Nonetheless, the value function is increasing in the outside option since agents choose their best option.

[17] To see this, note that a mother can attain J_{k-1} by setting $s_k = 0$ and chooses $s_k > 0$ only if this increases ex-ante expected gains. A higher R reduces the gains from the search for all (p_t, R), and p_t is equivalent to increasing the search horizon.

The model makes the following predictions we confirm in our data.

Prediction 1: Search intensity should increase in anticipation of an outside option being removed.

Prediction 2: Search intensity will increase as birth of the child approaches.

Prediction 3: As the deadline approaches, the reservation utility decreases so the willingness to accept worse matches increases, i.e. decision attention declines.

E.1 Evaluating welfare effects

To derive welfare implications of policy changes, we use equation (8). Consider legislation preventing mothers from having an abortion in the second trimester of pregnancy. These restrictions can be modeled either as changes in R_k, non-adoption options available, or as changes in p_k, the ability to delay adoption. Using the envelope theorem,[18] the effect of a change in p_{k+1} on the value function v_k is:

$$\frac{\partial v_k}{\partial p_{k+1}} = (1 - P(A_k))(v_{k+1} - R_{k+1}) \geq 0 \tag{9}$$

where $P(A_k)$ is the probability of adoption in period k. Intuitively, the welfare effect of changing the probability of being able to search is proportional to the probability of not finding a suitable family in the current period $(1 - P(A_k))$ and the forgone option value of being able to search versus having to take one of the non-adoption options $(v_{k+1} - R_{k+1})$. Similarly, the welfare effect of changing option R_{k+1} is:

$$\frac{\partial v_k}{\partial R_{k+1}} = (1 - P(A_k))(p_{k+1}\frac{\partial v_{k+1}}{\partial R} + 1 - p_{k+1}) \geq 0 \tag{10}$$

where $\frac{\partial v_{k+1}}{\partial R}$ accounts for the possibility that a change in R affects future value functions.

To illustrate the welfare effects, consider $p_{k+1} = 0$. That is, no adoptions are possible in period $k+1$. In that case, equation (5) collapses to $(1 - P(A_k))$. This is equivalent to Roy's

[18] We are assuming that the policy only affects p_{k+1} and exploit the fact that v_{k+1} depends on $p_{k+1+l}, l > 0$.

identity which shows that the welfare effect of a price change is proportional to the demand of the good.[19] Now consider the decision in period k-1 and assume for simplicity that $p_k = 1$ and $p_{k+1} = 0$. It follows that $\frac{\partial v_{k+1}}{\partial R_{k+1}} = (1 - P(A_{k-1})) \times (1 - P(A_k))$. In this model, the welfare effect of future changes in outside options decreases with the probability of finding a suitable adoptive family, which in turn, increases with periods of search. Thus, a birth mother can reduce the chance of negative effects in future outside options by searching for adoptive families earlier.

Some of the parameters in equations (9) and (10) can be estimated from the data, i.e. $P(A_k)$. However, the remaining parameters are not directly observable. Thus, we follow previous research (e.g. Chetty, 2009; Card et al., 2007) to derive welfare comparisons from observed behavioral changes by examining changes in search (s_k) due to policy changes.

Using the first-order conditions of equation (8), we obtain:

$$\frac{\partial s_k}{\partial p_{k+1}} = \frac{P(A_k)(v_{k+1} - R_{k+1})}{-c''(s_k)} \tag{11}$$

$$\frac{\partial s_k}{\partial R_{k+1}} = \frac{P(A_k)(p_{k-1}\frac{\partial v_{k+1}}{\partial R} + 1 - p_{k+1})}{-c''(s_k)} \tag{12}$$

The ratio of equations (11) and (12) provides the relative welfare effect of a change in p_{k+1} and R_{k+1}, i.e. the ratio of equations (9) and (10).

[19] The equivalence holds due to our assumption that search costs are separable.

F Effect of stimulus checks on search behavior

We quantify the effect of Dobbs by comparing it to the effect of Covid stimulus checks on search behavior. Stimulus checks were delivered on April 14-15, 2020, January 4, 2021 and March 12, 2021 (Chetty et al., 2024). The first check was $1,500 per adult and $500 per child. The second check was $600 per household member. The third check was $1,400 per adult and household dependent. Individuals with annual income below $75,000 qualified for the transfers in all three cases. In this section we concentrate on the effect of the stimulus checks on Black mothers living in ZIP codes with median income below $75,000. We use the 2014-2018 American Community Survey estimates of median household income by ZIP code. We concentrate on Black mothers because they are the most responsive to policy changes in our sample.

Figure F.1 and Table F.1 show the effect of Dobbs on search behavior for Black mothers living in ZIP codes with median income below $75,000. We observe an almost uniform reduction of child's age at first visit of 20 to 25 days. The median age at first visit for this group is 73.8 days and the effect of Dobbs is -25.5 (s.e. 9.40).

Table F.1: Effect of Dobbs on arrival time - Black mothers in ZIP codes with income less or equal to $75,000

	QUANTILE								
	10	20	30	40	50	60	70	80	90
Trigger ban states after June 24, 2022	-13.448	-22.454	-18.724	-23.209	-25.506	-27.936	-31.234	-27.724	10.502
	(10.543)	(12.473)	(13.326)	(10.848)	(9.395)	(9.631)	(11.203)	(12.930)	(32.381)
After June 24, 2022	-28.153	-30.526	-43.473	-42.753	-38.228	-32.158	-25.934	-21.634	-50.099
	(8.549)	(8.594)	(8.216)	(5.928)	(5.255)	(5.631)	(7.590)	(8.592)	(19.943)
Mother's age	-0.244	-0.328	0.182	-0.158	-0.495	-0.812	-1.169	-1.605	-3.281
	(0.512)	(0.609)	(0.589)	(0.486)	(0.360)	(0.379)	(0.479)	(0.621)	(1.390)
Trigger ban states	10.577	4.867	0.434	1.278	2.402	3.196	2.782	-3.540	-33.419
	(6.185)	(8.076)	(7.904)	(5.929)	(4.549)	(5.044)	(5.678)	(7.133)	(26.309)
Constant	-209.116	-164.379	-138.111	-101.449	-73.839	-48.454	-18.018	25.306	158.133
	(13.221)	(15.982)	(15.031)	(12.662)	(9.339)	(9.729)	(12.795)	(16.294)	(37.429)
Obs	2216	2216	2216	2216	2216	2216	2216	2216	2216

Notes: Quantile regressions. Dependent variable is age of child at initial inquiry in days. Standard errors in parentheses. Missing mother's age is replaced with zero and a dummy variable is included for missing data. Results are similar if we include all the data available. Regressions that control for the mothers' characteristics in the whole sample are in Table A.9.

Figure F.2 shows a time series of the average age of the child at arrival for this subpopulation with dates for delivery of stimulus checks marked by vertical lines. We observe that

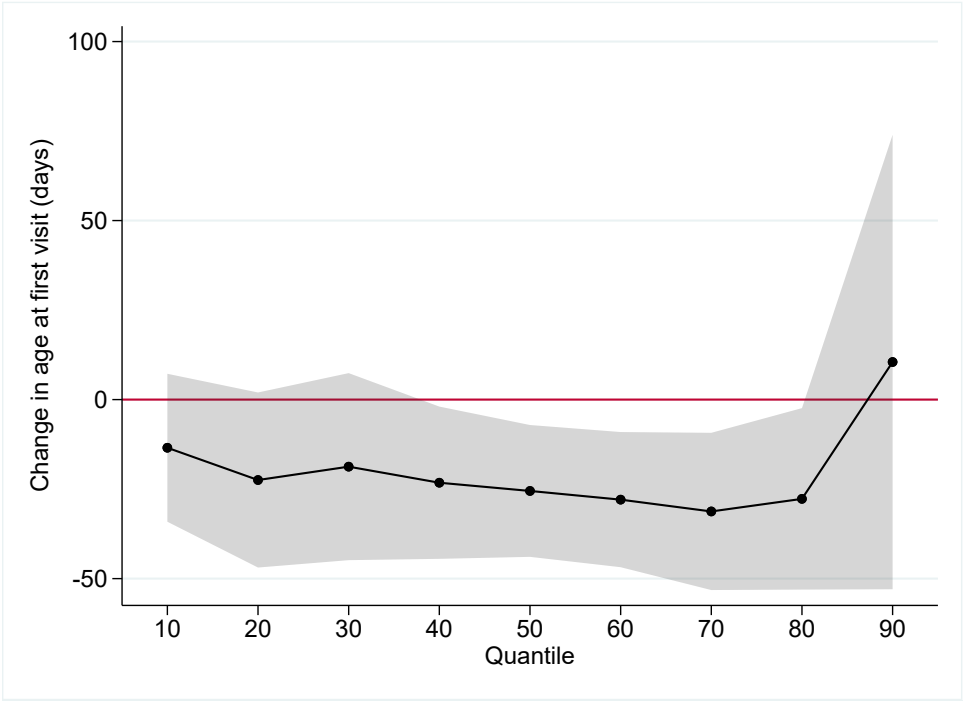


Figure F.1: Effect of Dobbs on arrival time - Black mothers in ZIP codes with income less or equal to $75,000

that receiving the stimulus checks tended to increase child's age at first visit, i.e., the checks diminished the incentive to search for adoptive families. The effects are, however, noisy and sometimes short-lived. To increase precision and reliability of our estimates, we estimate the effect of the stimulus checks simultaneously. That is, we stack our data and estimate the change in child's age after the stimulus check is delivered. Results using different bandwidths are presented in Figure F.3 and Table F.2. Standard errors are clustered at the birth mother level since, depending on the bandwidth, a mother can be simultaneously below and above a threshold. We observe that estimates are stable for bandwidth equal or greater then 30 days before and after the delivery of the stimulus check. The average child's age at arrival is around -77 days and the effect of the stimulus check is around 20-25 days. These results mimic closely those in Table F.1 for the median regression of the effect of Dobbs on age of child upon arrival. We emphasize that our analysis shows that Dobbs affected birth mothers decisions up to a year after the policy change. Our analysis of the effects of stimulus checks relies on a much smaller sample due to the research design we utilize to derive estimates.

Most of the mothers in our sample are single, and we have no information on whether they had other children. Thus, our back-of-the-envelope calculations assume the money received from the checks is what a single person would receive. The average stimulus check for a single person was $1,066.7. These stimulus checks increased the child's age at arrival temporarily by a magnitude similar, in absolute terms, to that of Dobbs. These stimulus checks, however, are likely a reflection of short term changes in economic conditions while Dobbs potentially captures a long-term effect. That is equivalent to a present value loss of $1,066.7.

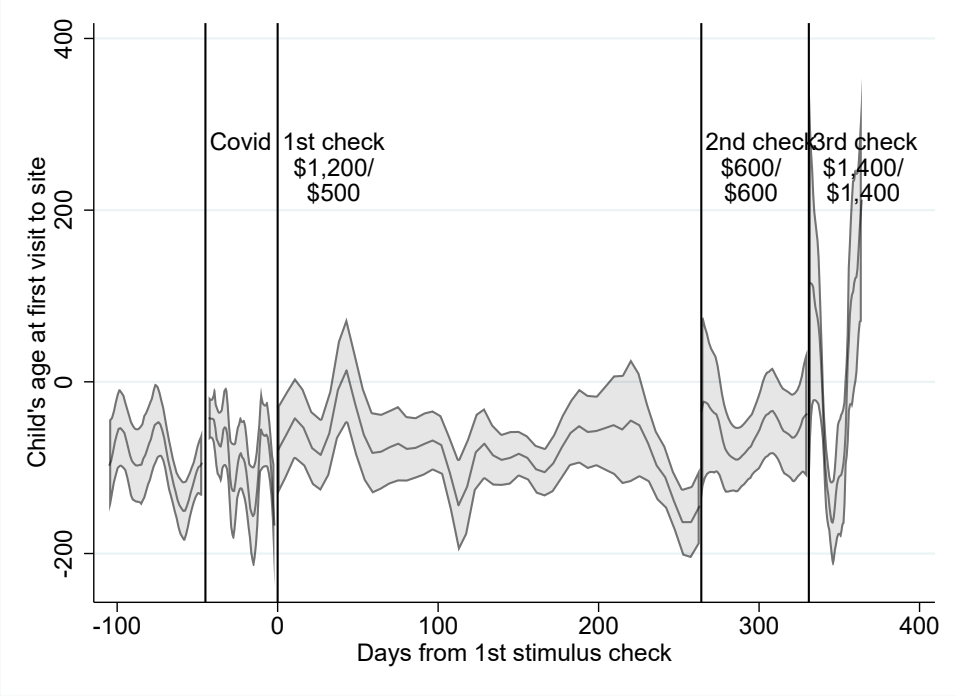


Figure F.2: Effect of stimulus checks on search behavior - Black mothers in ZIP codes with income less or equal to $75,000

Table F.2: Policy changes on search - Black mothers in ZIP codes with income less or equal to $75,000

	Bandwidth					
	20 days	30 days	40 days	50 days	60 days	70 days
1[After check delivery]	48.923	18.355	21.673	25.863	22.953	25.611
	(25.191)	(20.526)	(17.231)	(14.199)	(11.519)	(10.091)
Constant	-100.352	-83.341	-78.946	-77.765	-76.304	-77.600
	(13.413)	(12.944)	(10.812)	(9.371)	(9.004)	(8.082)
Obs	103	155	207	258	309	366

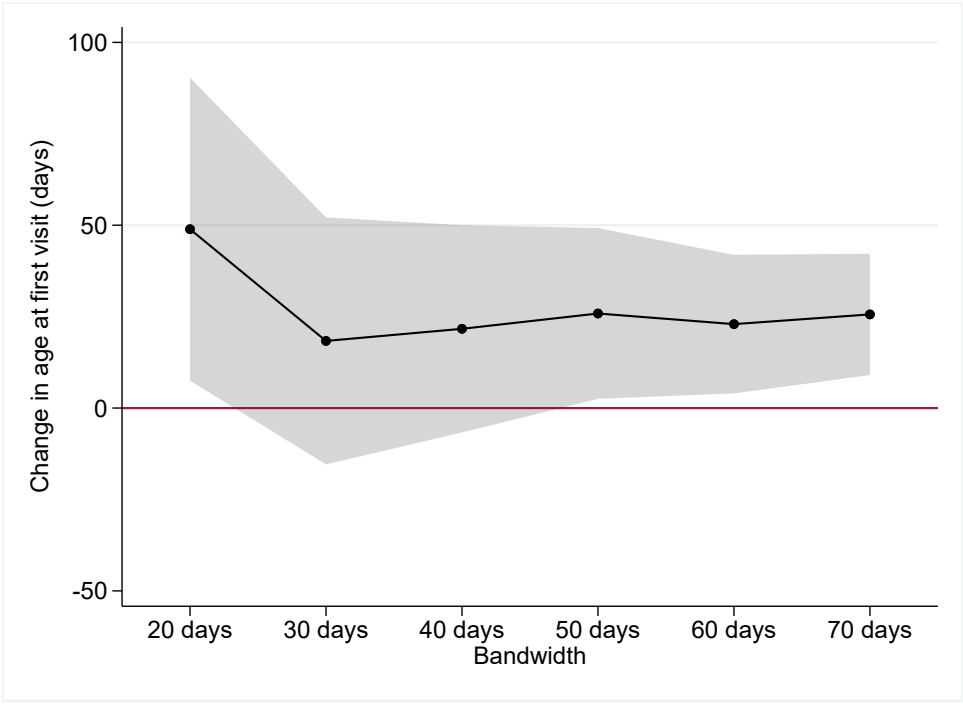


Figure F.3: Effect of stimulus checks on child's age at first visit for different bandwiths - Black mothers in ZIP codes with income less or equal to $75,000