War and Demand for Technology-driven Growth: Evidence from Ukraine

Natalia Lamberova* and Vera Mironova†

March, 2026

Abstract

War is often associated with accelerated technological change, even though its direct human and economic effects are overwhelmingly destructive. One reason may be political: war can make public investment in innovation more visible, urgent, and politically feasible than it is in peacetime. We study this mechanism in Ukraine using original wartime surveys that combine heterogeneous direct exposure to wartime harm with fixed-sum budget allocation tasks. Rather than comparing wartime to peacetime, we compare respondents who were more directly exposed to war to otherwise similar respondents from the same pre-war settlements and baseline socioeconomic profiles chosen to target the main observable predictors of exposure. More directly affected respondents allocate roughly 3–5 percentage points more of a reconstruction budget to R&D/technology. The financing margin differs by exposure type: economic harm primarily crowds out healthcare, while family harm primarily crowds out infrastructure. Direct exposure also reduces support for importing technology and increases the salience of domestic spillovers and scientific mobilization, while broad attitudes toward technology and a proxy for war support move little. The evidence is therefore difficult to reconcile with a generic rally-around-the-flag response and instead suggests that war can increase the political feasibility of public innovation.

JEL Classification: O31, O33, D74
Keywords: innovation, R&D, opinion, conflict

*University of Texas at Dallas, natalia.lamberova@utdallas.edu.
†Harvard, mironova.vera@gmail.com

1 Introduction

Wars damage countries' human and physical capital, destroying laboratories, displacing scientists, reducing their productivity, and increasing risk aversion. At the same time, wartime and the recovery that follows have often been moments of rapid technological advance: World War II and the Cold War yielded radar, jet propulsion, computing, GPS, and the internet; post-war Japan and South Korea reoriented toward technology-intensive growth with sustained state R&D. Numerous technological breakthroughs, such as civilian aviation, radar, antibiotics, the internet, and GPS, originated from government investments in wartime (Gross and Sampat, 2023; Ruttan, 2006).

A central reason technological progress accelerates in wartime is that war reshapes the political economy of innovation policy. In peacetime, governments can underinvest in R&D even when its social returns are high (Fieldhouse and Mertens, 2023; Dyevre, 2023). The returns from R&D investment typically materialize long after elected officials face reelection, making these investments less politically rewarding. In addition, innovation investment carries higher risk compared to more predictable and tangible alternatives such as infrastructure or education. By contrast, many alternative public investments generate outputs that are more immediately legible: voters can observe roads being built, services being expanded, or transfers being delivered. This creates an electoral incentive to prioritize policies with short-horizon, visible deliverables over innovation spending whose payoffs are less attributable within an electoral cycle. Wartime and reconstruction can relax this constraint by making technological capacity more salient and more immediately tied to security and recovery, thereby increasing the political feasibility of state-led innovation investments.

This political-economy mechanism matters only if public priorities can shape policy. A large literature shows that policy is responsive to policy-specific opinion, especially when issues are salient and electorally legible, even if responsiveness is imperfect and mediated by elites and organized interests (Wlezien, 1995; Burstein, 2003; Lax and Phillips, 2012). Our argument is therefore not that war mechanically determines innovation policy, but that exposure can shift mass demand in a way that changes the political feasibility of public R&D and related technology policies.

We study this argument in wartime Ukraine using original survey data that combine heterogeneous exposure to war with fixed-sum allocation tasks. Respondents allocate 100 points across competing reconstruction priorities, allowing us to observe not only whether support for technology rises, but which other priorities are displaced. We distinguish three exposure types: family exposure (a close relative killed, injured, or serving in the military), economic exposure (home damage or destruction, or forced displacement), and military exposure (active-duty service, with the military sample restricted to conscription-eligible men). Across exposure types, respondents with more direct wartime harm allocate 3–5 percentage points more of the reconstruction budget to R&D than observationally comparable respondents living under the same wartime environment but not directly harmed in the focal way. This shift appears to operate through reprioritization under scarcity rather than through a broad change in technology optimism or simple hawkishness: the evidence shows little corresponding movement in general attitudes toward technology, and only limited movement in preferred directions of technological change.

A post-war economic recovery depends not only on the extent of government R&D investment, but also on its direction. In the civilian sample, both exposure types are associated with stronger support for military technology, but the broader pattern is not a uniform shift away from civilian technologies. Family exposure is also associated with greater support for healthcare-related innovation and lower support for manufacturing, while economic exposure shows smaller and less systematic movements across the non-military categories. Among respondents on active military duty, preferences shift toward healthcare and, in some specifications, basic research, while support for additional military R&D is weaker. These patterns reinforce the broader conclusion that exposure changes strategic priorities over the direction of innovation rather than simply making respondents uniformly more hawkish or uniformly more pro-technology.

The way in which governments invest in R&D matters: countries below the technological frontier benefit from catch-up growth if they adopt existing technologies from abroad (Comin and Hobijn, 2011; Abramovitz, 1986; Boiko, 2019). Post-war periods often foster a drive towards domestic technological self-sufficiency rooted in national pride and security considerations (Luo, 2022; Odagiri, 1996; Kennedy, 2020). We investigate how

wartime experiences change the preferred choice over purchasing new technologies from abroad versus developing them domestically and the reasoning behind it, as well as preferences over conscription of scientists for active duty.

Ukraine, with its previously vulnerable innovation system, high human capital, and severe wartime disruptions, provides a uniquely informative setting in which to study the political feasibility of public innovation. We detail these background features below. Empirically, we compare exposed and unexposed respondents who share the same pre-war settlement and baseline socioeconomic profile, using a conditioning set chosen to target the main observable predictors of exposure.

Because direct exposure to wartime harm cannot be ethically or practically randomized, this study necessarily relies on observational variation in exposure. Accordingly, we do not treat wartime harm as randomly assigned. Instead, we compare respondents from the same pre-war settlements with similar baseline socioeconomic profiles and interpret the estimates under a selection-on-observables framework, supplemented by multiple matching strategies and sensitivity analyses. This approach is consistent with adjacent work on war and innovation, which likewise identifies effects from observational or quasi-experimental wartime shocks rather than randomized exposure. The evidence suggests that war can enhance the political feasibility of government R&D not by altering fundamental attitudes toward technology itself, but by reshaping public views about the government's role in fostering technological capacity and national resilience. Existing work on innovation policy often emphasizes firms, lobbies, and state institutions; we instead foreground the mass-political demand for innovation policy and show that wartime exposure shifts not just attitudes but budget trade-offs. More broadly, the paper contributes to the political economy of conflict by documenting a mechanism distinct from redistribution or generic state-building: exposure increases support for innovation-related public spending and strategic technological autonomy, with implications for long-run productivity and reconstruction.

The rest of the paper is organized as follows: Section 2 discusses the immediate effects of war on innovation, focusing on Ukraine and briefly discusses the state of Ukraine's pre-war innovation infrastructure. Section 3 discusses the data, measurement of the key treatment variable, identification assumptions and estimation. Section 4 presents the re-

sults. Section 5 discusses the robustness of the key results. Section 6 concludes.

2 Background

Social instability and political conflict impose significant burdens on economic outcomes, a relationship extensively documented in both cross-country analyses (Acemoglu and Robinson, 2001; Alesina et al., 1996; Barro, 1991; Mauro, 1995) and within-country studies (Abadie and Gardeazabal, 2003). Historical evidence further demonstrates that conflicts have enduring adverse effects on international economic interactions, notably by decreasing international trade volumes and weakening economic integration even decades after hostilities end (Guiso et al., 2009).

Beyond broad economic effects, wars profoundly impair innovation directly by undermining human capital essential for research and technological development. Empirical evidence highlights that exposure to violence significantly reduces researchers' productivity: affected researchers produce fewer publications (Chen and Moser, 2024) and patent applications (Cook, 2014). Stress and mental health challenges, which commonly accompany war experiences, further compound this negative impact on research productivity (Biasi et al., 2021).

A secondary channel through which war may stifle innovation is by altering individual risk preferences. Innovation inherently involves uncertainty: even rigorous research efforts and promising ideas often fail (Harhoff et al., 1999). The inherent uncertainty in innovation is evident from startup failure rates, where approximately half fail within five years, and only a third survive a decade (U.S. Small Business Administration, Office of Advocacy, 2023). Consequently, if conflict-induced trauma heightens risk aversion, individuals may shift their preferences toward safer, less ambitious projects (Moya, 2018; Lerner and Keltner, 2001; Callen et al., 2014). Recent evidence in economic history points to precisely this mechanism. Using parish-level WWI mortality shocks in Britain linked to patent and inventor data, Repetto et al. (2026) show that wartime human-capital losses produced persistent declines in local patenting, with especially large effects on breakthrough innovation. They further show that these effects operated through both lower productivity of incumbent inventors and weaker entry of new inventors, consistent with

a supply-side human-capital channel. This mechanism is distinct from the one we study here: even if war damages the innovation base itself, direct wartime exposure may still increase public support for state-led technology investment during reconstruction.

Even before the 2022 escalation, Ukraine's innovation system was structurally weak. Gross R&D fell from 1.07% of GDP (2003) to 0.41% (2020); business R&D accounted for only about 20% of total (0.08% of GDP) and was largely self-financed (World Bank, 2025). The 2019 National Innovation Strategy's action plan was only partially implemented and lacked a monitoring mechanism; rule of law, investor protection, credit to the private sector, and outdated infrastructure - constraining firm- level innovation (for Economic Co-operation and Development, 2022).

At the same time, Ukraine retained important assets. Tertiary enrollment was high (about 83%) and ICT services were dynamic: exports increased to $7.1 billion in 2021 (38% of service exports), although activity remained concentrated in low valueâadded outsourcing; Intellectual property license receipts were just $69 million in 2021, down from $167 million in 2013 (for Economic Co-operation and Development, 2022; World Bank, 2022, 2024). The broader industrial base remained diverse but resource - biased: agriculture accounted for 41% of merchandise exports in 2021 (overtaking metallurgy's historical role) (Service, 2024).

The onset of full-scale invasion in 2022 severely disrupted Ukraine's innovation ecosystem, particularly affecting its research sector. Assessments of Ukraine's scientific community during wartime (for Economic Co-operation and Development, 2022; Suchikova et al., 2023; Bezvershenko et al., 2025) indicate that roughly one-quarter of the country's research workforce emigrated within the initial seven months of conflict - nearly twice the general population's emigration rate of 13.5%. Researchers who stayed faced significant impediments, including displacement, instability, and psychological distress, which substantially reduced their scientific productivity.

Moreover, the war abruptly terminated critical international scientific collaborations, notably between Ukrainian and Russian researchers, historically a substantial portion of Ukraine's internationally co-authored publications. Losing these collaborations severely isolated Ukrainian science from critical networks, funding opportunities, and shared infrastructure. Collectively, these factors - pre-existing structural fragility, wartime emigra-

tion of scientists, disruption of international collaborations, and severe physical and psychological impacts -make Ukraine a uniquely important case for exploring the interplay between technological development and armed conflict.

The war's profound human costs - ranging from direct exposure to forced displacement - have further influenced broader national identity and political transformation processes. Recent research suggests that the conflict accelerated nation-building, reinforcing Ukrainian national identity while reducing linguistic and cultural affiliations with Russia (Dill et al., 2023; Abramenko et al., 2024). Specifically, Abramenko et al. (2024) demonstrate that wartime experiences have led many Ukrainians to shift from Russian to Ukrainian language usage on social media, coinciding with increased self-identification as Ukrainian in surveys [1]. These shifts may shift the preference towards domestic technology development away from importing technology.

3 Data and Methods

This study draws on two surveys ae have conducted in wartime Ukraine: our civilian sample comes from the Kyiv International Institute of Sociology (KIIS) Omnibus survey fielded in February 2024. The sample comprises 2000 adult respondents who provided informed consent. Participation was voluntary, withdrawal was permitted at any time, and enumerators were trained to ensure the safety of both interviewers and respondents (Cronin-Furman and Lake, 2018). To prioritize safety, we assured our Ukrainian partners that any interview interrupted for security reasons would carry no repercussions, financial or otherwise.

The civilian sampling frame is adults aged 18 and older living in government-controlled territory at the time of data collection. KIIS designed the sample to be representative within this frame. The survey does not capture all exposed Ukrainians: in areas previously under Russian occupation, exposure rates were higher, and only those who relocated into government-controlled territory could be observed. Ukrainians who left the country are not included.

[1] However, the impact of war on social and political attitudes is nuanced: Hoch et al. (2025) find that objective experiences of Ukrainian war events correlate negatively with prosocial behavior and institutional trust, whereas subjective, trauma-based experiences exhibit a positive association with prosociality

In addition to the KIIS civilian survey, we fielded a survey of 300 active - duty servicemembers in June 2024. For these respondents, we observe pre-war location at the *oblast* (region) level and age; pre-war occupation is unavailable.

Conscription was driven by *age*, *gender* and *geographic location*. Under martial law, Ukraine operated mandatory mobilization. Men aged 18 - 60 could serve, with compulsory draft eligibility applying to older cohorts; the statutory minimum age for mobilization was lowered from 27 to 25 in April 2024 (Verkhovna Rada of Ukraine, 2024). At the time of our survey, roughly 25% of service personnel were volunteers and 75% were conscripts, so the armed forces were predominantly conscripted (Petrenko, 2024).

Because voluntary service below the mobilization threshold may be selectively chosen, we **trim the military sample to conscription-eligible men** (ages 25 - 60 as of June 2024). Women were not subject to conscription by law; those serving did so voluntarily. Although women constitute an estimated 15% of active military personnel, the absence of a female conscription comparison group leads us to restrict the analysis to men. We do not observe conscript/volunteer status at the individual level; however, given the aggregate composition, the share of volunteers in the trimmed sample is likely small, which helps mitigate selection into service.

Mobilization is administered locally through Territorial Recruitment and Social Support Centers (TRCs): district and city TRCs "organize and maintain military registration on the territory of the relevant administrativeâterritorial unit," and individuals are registered with the TRC at their declared place of residence; TRCs are established at the oblast/city/district levels (Cabinet of Ministers of Ukraine, 2022). Together, these rules imply that eligibility is age-based, while *who* calls a person (and when) is determined by the TRC responsible for that person's place of residence.

3.1 Measuring Exposure to War

The Russian invasion of Ukraine in February 2022 has affected the entire population, although individual experiences of exposure vary significantly. To measure these variations, respondents were asked:

The war has brought devastation to the whole country, hurting some people more than

others. Please select all that apply to you: I was wounded; An immediate family member was wounded or killed; Immediate family member is currently serving in the army; My home was damaged or destroyed; I was forced to flee my home; None of the above

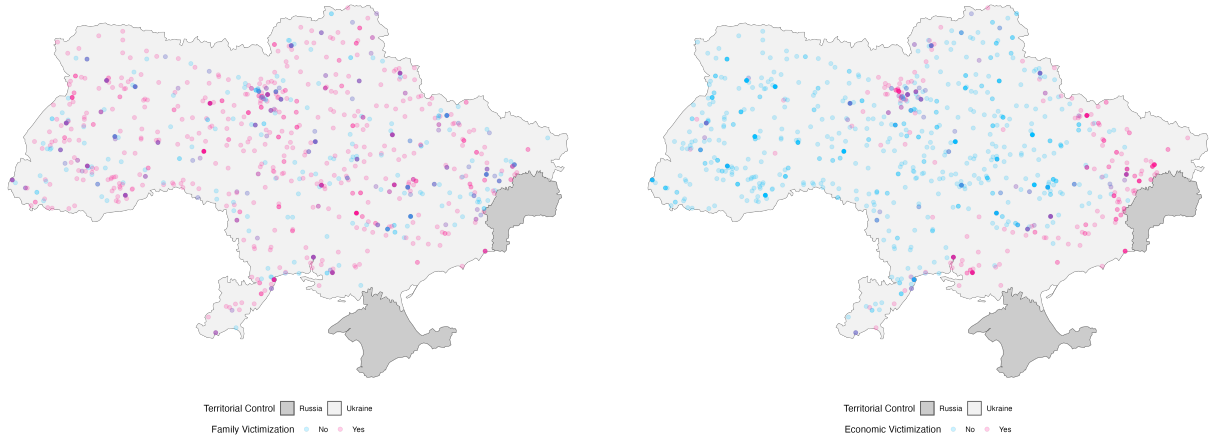
.

In our survey sample of 2,000 respondents, only 39 individuals reported personal injuries, limiting statistical reliability for analyzing direct personal exposure. Figure A.1 illustrates results from a principal component analysis (PCA) of the remaining exposure types, revealing distinct groupings: respondents experiencing economic harm (home damage or forced displacement) cluster together; individuals with family members killed, injured, or currently serving in the army form another distinct group; and respondents unaffected by these exposure types clearly form a separate control group.

Consequently, respondents are grouped into three categories: Control (respondents selecting "None of the above"), Economic exposure (respondents experiencing home damage or displacement), and Family exposure (respondents whose family members were killed, injured, or are serving in the army).

This separation is motivated methodologically and theoretically. First, economic and family exposure likely have different implications for policy preferences: economically harmed individuals might prioritize policies promoting economic recovery, while family-exposed individuals may emphasize military readiness and healthcare investment. Second, these exposure types have distinct assignment mechanisms: economic harm primarily results from Russian aerial strikes, whereas family exposure relates to Ukrainian conscription practices. As will be discussed further in the Results section, the findings derived from these two exposure types remain broadly consistent with each other. Figure 1 presents a map of exposure patterns for the civilian sample. The panels show respondent locations by exposure status for the civilian sample, including respondents reporting economic exposure, family exposure, and those selecting "none of the above."

Understanding the specific type of exposure is crucial because prior research suggests it can distinctly influence risk tolerance and policy preferences, which in turn shape preferences over government investment in innovation and the desired direction of innova-



(a) Family exposure

(b) Economic exposure

Figure 1: Spatial distribution of exposure in Ukraine, 2022. Each dot marks a respondent location. Magenta denotes 1 treated and cyan denotes 0 control. Family exposure equals 1 if a family member was killed, injured, or is currently serving in the army. Economic exposure equals 1 if a home was destroyed or the respondent was forced to flee. Maps are descriptive and do not adjust for population or sampling density.

tion policy.

The existing literature demonstrates various effects of violence exposure on risk preferences. In Colombia's prolonged civil conflict, survivors of violence displayed significantly increased risk aversion compared to similar not directly exposed individuals (Moya, 2018), a pattern closely linked to anxiety and PTSD symptoms (Lerner and Keltner, 2001). Similarly, Callen et al. (2014) observed a pronounced "certainty premium" among Afghan civilians exposed to Taliban insurgency violence, as these individuals strongly preferred guaranteed payoffs even when uncertain options had higher expected returns [2]. Table C.1 presents a brief summary of select papers on the effects of war exposure, highlighting different approaches to defining what constitutes a treatment. Displacement, family member being killed or injured, participation in the active military, as well as being personally injured constitute the most common approached to defining exposure. People

[2]However, findings from other contexts have differed. Voors et al. (2012) showed that individuals in post-conflict rural Burundi exhibited greater risk tolerance in experimental settings compared to those not exposed to violence. Kibris and Uler (2023) reconcile these contrasting findings through a natural experiment involving Turkish conscripts randomly assigned to high- or low-conflict regions. Soldiers deployed in combat zones generally showed increased risk tolerance, reflecting adaptation to risky environments, yet those directly experiencing traumatic violenceâsuch as combat injuries or witnessing comrades' deathsâbecame significantly more risk-averse

living in Ukraine at the time of war and not reporting any type of direct exposure are considered a control group for the purposes of this study, despite exposure to ambient effects of war. Summary statistics of the key demographic variables, as well as treatment status and census weights is presented in Table B.1 of the Appendix.

3.2 Identification: Conditionally Indiscriminate exposure

The war that Russia launched against Ukraine in February 2022 has been marked not only by large-scale military operations but also by extensive and indiscriminate violence targeting civilians and civilian infrastructure. Russian forces have repeatedly employed unguided artillery, cluster munitions, and aerial bombardments in densely populated areas, resulting in devastating civilian casualties and widespread destruction of homes, hospitals, and schools (OHCHR, 2023; International, 2023). Beyond physical destruction, the war has also unleashed pervasive gender-based violence, including conflict-related sexual violence. Russian soldiers have systematically committed acts of rape, sexual slavery, and forced nudity, often as part of broader campaigns aimed at terrorizing and degrading civilian populations (Weber, 2023; Watch, 2024). These patterns of indiscriminate violence and systematic gendered abuse have inflicted severe social and psychological scars, while also shaping public perceptions of the state, the military, and the future of the country.

The indiscriminate nature of Russian military violence across settlements and gender groups creates quasi-random exposure to conflict intensity, conditional on a person's pre-war location, age and occupation, enabling the use of natural experimental approaches to study how direct and indirect exposure to violence shapes attitudes toward technology, innovation policy, and the role of science in post-war reconstruction. Our survey samples respondents residing in government-controlled territory at the time of fieldwork. The sample therefore includes both individuals whose pre-war communities were never occupied and individuals who relocated from areas that later became occupied; it does not include individuals residing under occupation at the time of the survey. Accordingly, our estimand is the effect of wartime exposure on policy preferences among residents of government-controlled territory—the population whose attitudes are most directly relevant for reconstruction policy. In this sense, Ukraine's tragedy offers a rare opportunity to

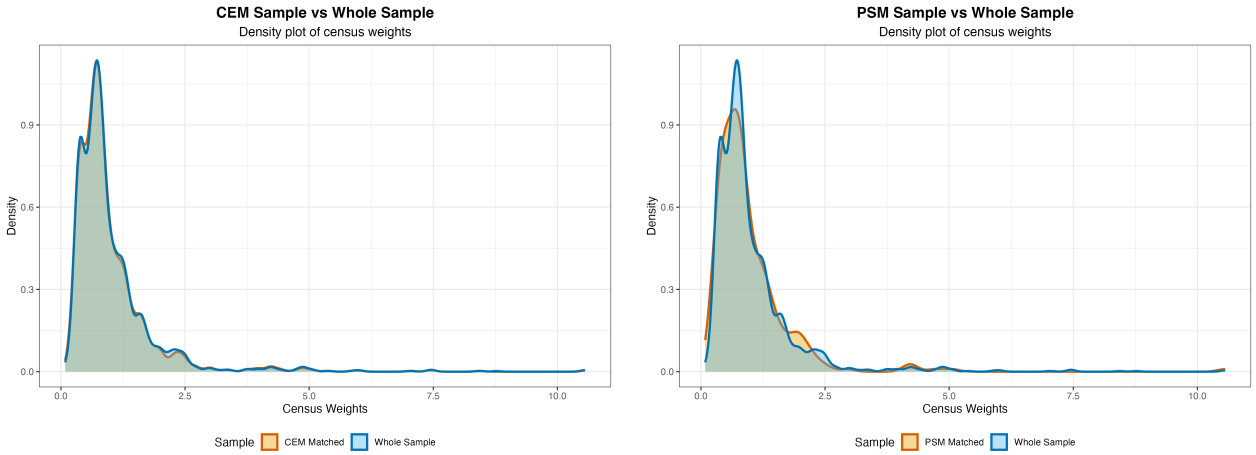
study how personal exposure interacts with broader processes of technological development and national recovery, contributing to both the political economy of innovation and the study of post-conflict recovery.

To assess the plausibility of this conditioning strategy, we document overlap and balance for exposed and unexposed respondents within pre-war settlements. Figure 3 (and Appendix Figure D.1 for Economic exposure) reports propensity-score overlap diagnostics under our specification; Appendix balance tables report standardized mean differences for the matched samples. The key empirical fact is that once comparisons are structured within pre-war settlements and conditioned on baseline socioeconomic profile, exposed and unexposed respondents exhibit substantial common support, reducing reliance on extrapolation across fundamentally different local contexts. Exposure to wartime harm is not randomly assigned across Ukraine, but much of the systematic variation operates at the level of pre-war place and baseline socioeconomic position. We therefore structure comparisons within respondents' *pre-war settlement*, which absorbs locality-level determinants of both exposure risk and baseline preferences (prewar development, local labor markets, infrastructure, distance to frontline), while avoiding post-treatment conditioning that would arise from using current residence. Within settlements, we condition on pre-treatment demographics and socioeconomic characteristics - in particular education and occupation - chosen to address the most plausible within-settlement confounding channel in larger localities: baseline socioeconomic sorting that shapes both (i) where people live and work within a settlement and thus their exposure risk, and (ii) baseline orientation toward technology, innovation, and the role of the state in reconstruction. Conditional on pre-war settlement and this pre-treatment profile, remaining variation in direct exposure (e.g., whether a home is damaged or a family member is harmed) plausibly reflects the realized incidence of violence rather than latent tastes for allocating a fixed recovery budget toward R&D. We interpret the resulting estimates as causal under a standard selection-on-observables assumption and quantify robustness to residual confounding using Oster coefficient-stability bounds and Rosenbaum sensitivity analysis (Appendix Tables F.1 and G.1). If our identification strategy holds, then after accounting for settlement and gender, the distributions of propensity scores for exposed and not directly exposed individuals should be similar. To verify this, we first condition on settlement and gender and

then inspect the propensity score distributions separately. Under proper identification assumptions, differences in these distributions after conditioning on settlement and gender should be minimal, as settlement characteristics largely determine exposure to conflict.

We estimate propensity scores by running a logistic regression of exposure status (Economic or Family) on pre-treatment covariates. The resulting scores provide the estimated probability of experiencing each exposure type for each individual. Figure 3 presents the results for Family exposure, Figure D.1 of the Appendix provides results for Economic exposure. The top row of Figure 3 illustrates these gender-specific distributions of propensity scores before reweighting for settlement for Family exposure. Initially, the distributions differ substantially between groups. However, these differences are unsurprising, as settlement location largely dictates exposure probabilities. When we reweight respondents within the control group to match the settlement distribution of those directky exposed, we achieve satisfactory - though imperfect - balance, suggesting that our conditioning effectively accounts for geographic differences driving exposure. Similarly, The top row of Figure D.1 illustrates these gender-specific distributions of propensity scores before reweighting for settlement for Economic exposure. The bottom row presents the reweighted propensity score distributions, which are much better balanced.

After accounting for pre-war settlement and baseline covariates, treated and control propensity-score distributions still differ enough to make unadjusted comparisons unattractive. We therefore estimate effects using three complementary designs: Coarsened Exact Matching (CEM), one-to-one nearest-neighbor propensity-score matching (PSM), and kernel balancing. Across civilian specifications, the conditioning set includes pre-war settlement, gender, age, education, and occupation, chosen to target the main observable predictors of exposure. In the military sample, where covariate information is more limited, we match on pre-war location and age and restrict attention to men of conscription-eligible age. Our baseline PSM design is one-to-one nearest-neighbor matching with replacement within pre-war settlement, with standard errors clustered at the matched control identifier. Exact matching within pre-war settlement restricts the analysis to settlements with common support; the baseline design retains the majority of treated observations for economic exposure and a smaller but still substantial matched sample for family harm (Appendix Table H1). Because Ukraine contains many small settlements with few



(a) CEM: matched vs whole sample

(b) PSM: matched vs whole sample

Figure 2: Density of census weights. The matched-sample density closely overlaps the whole-sample density in both CEM and PSM. Similar shapes and tails indicate that matching does not rely on extreme-weight cases.

respondents, some treated observations necessarily fall outside support. The resulting estimates should therefore be interpreted as effects for the treated respondents observed within overlapping settlements.

The main concern with employing matching techniques, is that the retained units are systematically different from the rest of the sample in a way that is related to the outcome. For example, it is easier to find a match in a bigger settlement than in a small village - but people from large cities can have different attitudes toward government R&D investment and its preferred direction, different attitudes toward technology and technology-related policies, leading to sample-selection bias. We cannot test the representativeness of the matched sample on all possible relevant variables. Beyond matching and balancing covariates, we do not have access to pre-treatment outcomes to test the achieved balance. Hence, we utilize the Census Weights KIIS provides with its omnibus survey for all respondents.

Figure 2 compares the kernel densities of census weights in the whole survey and in the matched samples. The curves almost coincide. The matched samples do not overrepresent very large or very small weights. The right tails align with the full sample. Matching therefore does not concentrate on unusual or unrepresentative observations, at least along this dimension.

3.3 Matching and Balancing

Our outcome is the share of a post-war budget that respondents allocate to R&D. The treatment is wartime exposure (casualty or property/displacement), which is not randomly assigned. We therefore rely on adjustment for observables under conditional ignorability and overlap (Rosenbaum and Rubin, 1983; Rubin, 2008). To reduce model dependence and to probe robustness, we implement *three complementary design strategies*: Coarsened Exact Matching (CEM), Propensity-Score methods (PSM), and Kernel Balancing (KBal). We keep the estimand fixed as the ATT,

$$\tau = \mathbb{E}\big[Y(1) - Y(0) \mid T = 1\big],$$

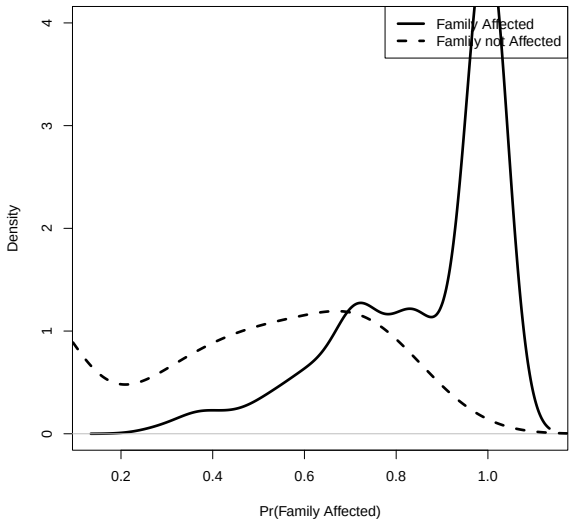
and judge success by balance diagnostics (standardized mean differences, variance ratios), effective sample size, and overlap plots (Stuart, 2010; Austin, 2011; Crump et al., 2009). Using multiple, principled designs is a form of triangulation that guards against researchâdesign dependence (Steegen et al., 2016).

CEM discretizes pre-treatment covariates into bins chosen *ex ante* and forms exact matches within coarsened strata, dropping observations outside common support and reweighting the remainder (Iacus et al., 2012). We use CEM to (i) impose transparent, monotonic bounds on imbalance by design (the MIB property), and (ii) trim regions with weak overlap that would otherwise drive extrapolation (Iacus et al., 2012; Crump et al., 2009). Because results can depend on cutpoints, CEM alone is not our final estimator (Black et al., 2022).

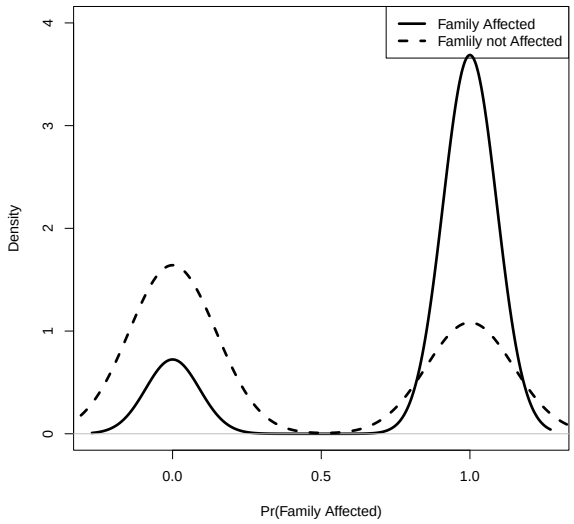
PSM reduces high-dimensional adjustment to a scalar propensity score $e(X)$ and then matches treated respondents to observationally similar controls on $\hat{e}(X)$ (Rosenbaum and Rubin, 1983; Stuart, 2010; Ho et al., 2007). Our implementation uses one-to-one nearest-neighbor matching with replacement within pre-war settlement, which allows us to preserve transparent treated–control comparisons while respecting the strongest geographic source of exposure assignment. PSM therefore provides a design-based estimate of the ATT that is easy to interpret and directly comparable to CEM and KBAL. Appendix Table E.1 presents balance diagnostics for the matched samples, and Table H1 reports matched-sample coverage. Common support is more limited for family than for economic expo-

sure, consistent with family harm being more spatially concentrated across settlements; those estimates therefore identify effects for the subset of treated respondents observed in settlements where both exposed and unexposed individuals are present.

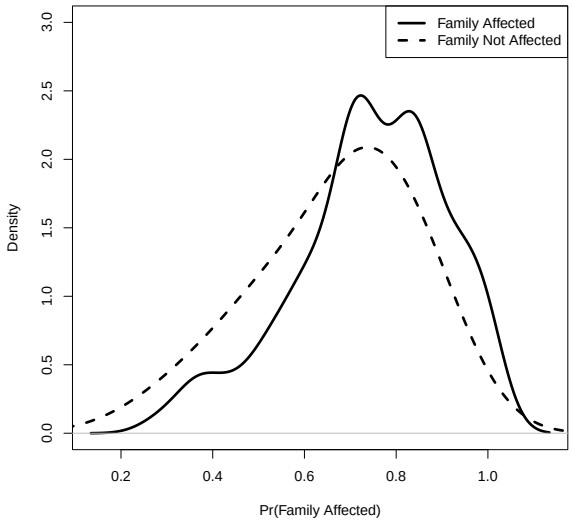
Kernel Balancing chooses nonnegative weights on controls so that the treated and weighted controls have (approximately) equal means on a rich set of nonlinear features induced by gaussian kernel; when the nonâtreatment potential outcome lies in the corresponding Hilbert kernel space, the ATT is unbiased and remaining bias is bounded (Hazlett, 2020). KBAL directly targets mean balance in a high-dimensional function space, addressing nonlinear confounding without manual specification of interactions. Agreement of estimates across these approaches materially strengthens the credibility of our causal claims (Rubin, 2008; Steegen et al., 2016).



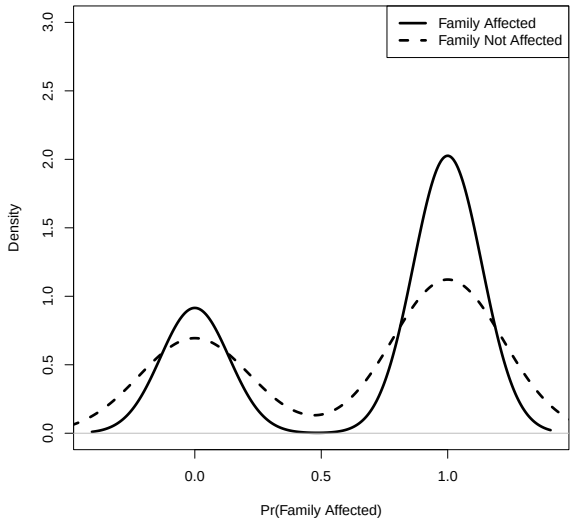
(a) Unweighted Male Family Harm



(b) Unweighted Female Family Harm



(c) Reweighted Male



(d) Reweighted Female

Figure 3: Propensity Score Distributions for treated and untreated: family harmed

Notes: Propensity scores distributions for the Family Harm. Top panel - Top panel â Without controlling for settlement, the propensity score model differentiates individuals likely to experience family harm from those who are not based on their covariates. Bottom panel â After weighting the data, the propensity score distributions of harmed and unharmed individuals become more similar.

4 Results

There are several groups of outcomes we consider in the study. The first group reflects the preferences over allocation of hypothetical post-war reconstruction budget towards innovation, and direction of investment in technology. The second group reflects broad attitudes towards technology and its role in society, attitudes towards technological sovereignty, and attitudes towards the role scientists during the war. Finally, we explore considerations that drive preferences over investment in domestic versus purchasing foreign technology. We describe both measurement of these outcomes and theoretical expectations below. We report all results for both types of war exposure.

4.1 Preferences over Budget Allocation

Our main outcome of interest is respondents' preferences regarding government budget allocation during post-war reconstruction. Specifically, we asked participants to distribute a hypothetical budget of 100 units across several spending prioritiesâhealthcare, infrastructure, technology, education, and tax relief. This design captures not only the share of resources respondents allocate to technological development but also their relative trade-offs across competing priorities, while tax relief category allows respondents who prefer a different, non-listed spending category to reflect their preferences through lower allocations to the listed options.

During peacetime, public support for government spending is often mixed: citizens tend to resist higher taxation yet are reluctant to cut valued programs, including social welfare benefits (Branham and Jessee, 2017; Tuxhorn and Kurzban, 2021). Wartime contexts typically shift this equilibrium. Governments can raise revenues more readily when conflict heightens collective purpose and reduces opposition to taxation (Besley and Persson, 2009). Major wars have historically expanded fiscal capacity through new taxes, debt financing, and broader acceptance of state intervention (Bank and Thorndike, 2008; Tilly, 1975). In our design, other spending categories capture this general rally-around-the-flag effect, allowing us to interpret higher allocations to R&D as evidence of a distinct preference for technology-driven reconstruction rather than a generic rise in support for public spending. We specifically analyze and report only the share of budget respondents allo-

cate to technological development.

Figure 4 reports average treatment effects on the treated (ATT) for the willingness to invest in technology. Squares, circles, and triangles denote CEM, PSM, and KBAL; horizontal bars are 90% confidence intervals. Respondents with *Econ* exposure prefer government R&D expenditures to be roughly 2-4 units higher relative to control. The effects of *Family* exposure are again positive, about 1.5-3.5 units, with overlapping intervals. These magnitudes are substantively similar across types pf exposure and estimators. They are also substantively meaningful - in developed countries, total R&D expenditures rarely exceed 2.5% of GDP.

The effects of active military service are larger. The *Military None* contrast compares respondents on active military duty to unharmed civilians. Point estimates are about 6–8 units and clearly exceed the civilian effects, though the intervals are wide. The *Military Exposed* contrast is harder to interpret causally because it conditions on other exposure types, which are plausibly post-treatment. Still, it is descriptively useful: it compares service members to civilians matched on exposure status as well as location and age, helping isolate the component of the difference more directly associated with service. The estimates remain positive but are smaller, about 4–6 units. This attenuation is expected because matching on exposure absorbs part of the difference attributable to harm and displacement rather than service per se.

Across designs the sign is stable and positive. The biggest effects come from conscription into military, the lowest - from family exposure. Uncertainty is greatest in the military samples, reflecting smaller effective sample sizes.

To further clarify respondents' attitudes toward technological priorities, we asked them to allocate 100 hypothetical units of government spending across five distinct categories of technological progress: Information Technology (IT) and Artificial Intelligence (AI); Healthcare Innovation; Military Technology; Advanced Manufacturing; and Basic Research (e.g., theoretical physics and mathematics). These precise allocations serve as direct measures of preferred directions for technological development in Ukraine's post-war context.

Figure 5 displays ATT coefficients for five R&D categories (Basic Tech, Manufacturing, AI & Communication, Healthcare, Military) across four samples: Economic exposure,

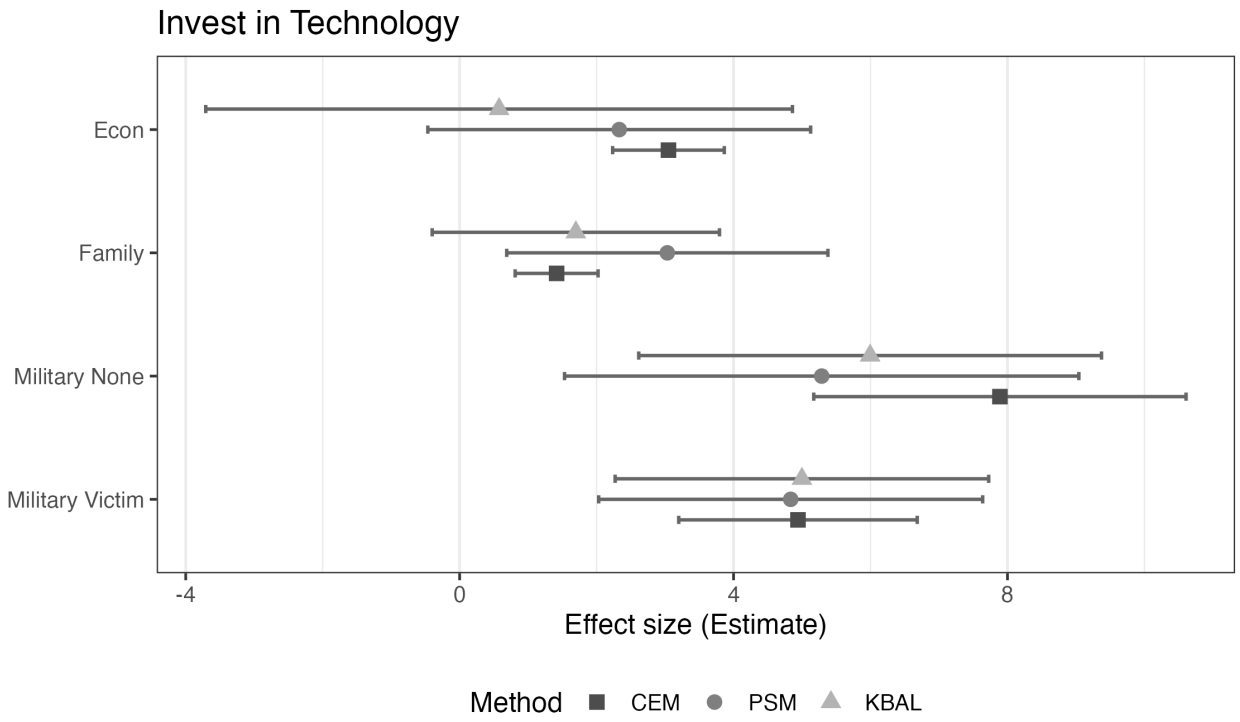


Figure 4: ATT estimates for the outcome "Invest in Technology." Shapes mark estimators (CEM, PSM, KBAL); bars show 90% confidence intervals. Civilian contrasts (Econ, Family) yield positive effects of about 2-4 and 1.5-3.5 units, respectively. Military contrasts are larger: *Military None* is about 6-8 units; *Military Exposed* is about 4-6 units. The attenuation in *Military Exposed* reflects matching on exposure, which absorbs exposure-related differences.

Family exposure, Military - None, and Military - Exposed. Squares, circles, and triangles correspond to CEM, PSM, and KBAL; bars are 90% CIs.

In the civilian panels (Economic and Family exposure), the clearest positive shift is toward Military R&D. Movements in the civilian technology categories are more mixed. Family exposure is associated with more support for Healthcare and lower support for Manufacturing, while Economic exposure shows smaller and less systematic reallocations across the non-military categories.

In the military panels, the strongest positive shifts are toward Healthcare, with Basic Tech also positive in the Military-Exposed sample. Manufacturing and AI & Communication are mixed. Overall, exposure changes the preferred direction of innovation, but not in a way that can be summarized as a uniform shift toward either military or civilian technologies.

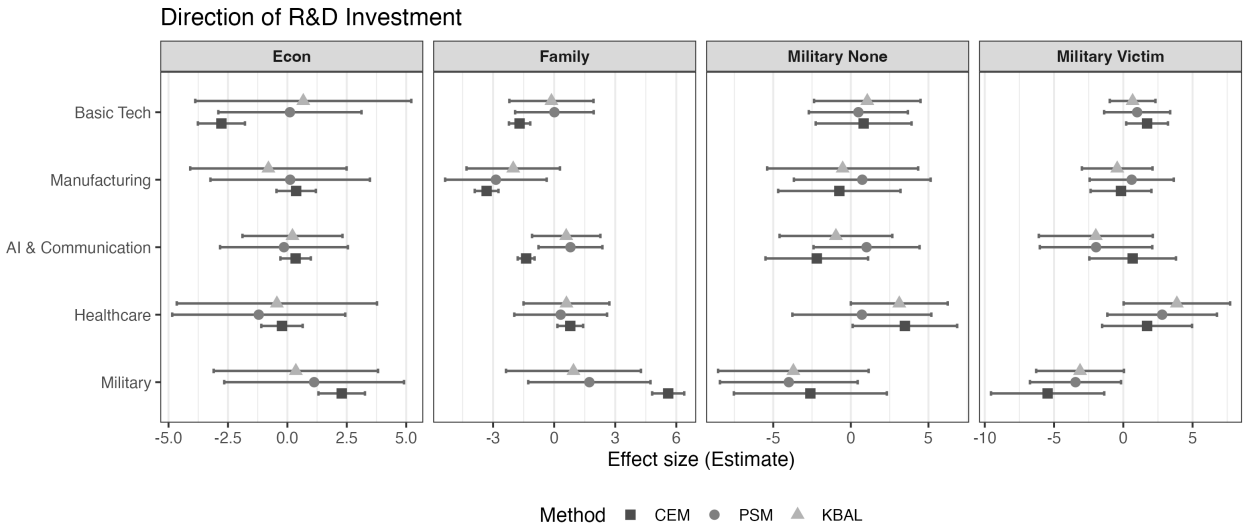


Figure 5: Direction of R&D investment: ATT estimates by category and sample. Points denote CEM (square), PSM (circle), and KBAL (triangle); bars are 90% confidence intervals. Civilian samples show a clear positive shift toward Military R&D, with mixed movements in the other categories. Military samples show positive shifts in Healthcare (and, for Military-Exposed, also in Basic Tech), while Manufacturing and AI & Communication are mixed.

The way in which technology is acquired matters - Ukraine could benefit from catch-up growth if it relied on foreign technology for reconstruction. The next set of questions sheds light on the effect of war on the preferences for investing in domestic technological capacity vs purchasing technology from abroad, and a related issue - should scientists be conscripted for active military duty.

Purchase technology from abroad or build technologies domestically. Conscription of Scientists

The war with Russia has accelerated nation - building processes within Ukraine, emphasizing Ukrainian identity and sovereignty (Dill et al., 2023; Abramenko et al., 2024). Yet, it remains unclear whether this strengthening of national identity translates into preferences about technology acquisition. A crucial dilemma facing countries behind the technological frontier is whether to develop domestic technologies independently or to import established technologies from abroad. To capture preferences on this issue, we explicitly ask respondents whether they prefer acquiring existing technology from abroad or developing domestic technological capacity. We create a dummy variable that takes value

of 1 if the respondent prefers to purchase existing technology, 0 if they prefer to build new technology domestically. A related question is attitudes towards conscription of scientists. The war has severely disrupted Ukraine's scientific community, with approximately 25% of researchers emigrating within the first months of the conflict (for Economic Co-operation and Development, 2022; Suchikova et al., 2023; Bezvershenko et al., 2025). Against this backdrop, conscripting scientists into military service carries significant risks for Ukraine's long-term recovery and technological capacity.

We measure attitudes towards the conscription of scientists by asking respondents to indicate their level of agreement (on a 5-point Likert Scale) with statements such as whether scientists should be conscripted during wartime. Specifically, respondents assessed whether scientists, distinguished by categories such as well-known figures or those working in crucial sectors like healthcare, should serve in the military or be exempted due to their value to post-war recovery. For the sake of brevity, we focus on preferences for conscription of scientists "from all fields of study", though the results are consistent across options.

Theoretically, exposure by the war could drive respondents to shield scientists, recognizing their importance for the nation's reconstruction. Conversely, exposure could foster a preference for more equitable sharing of the warâs burdens, advocating equal responsibility across all societal groups.

Figure 6 reports average treatment effects on the treated (ATT) for two outcomes: *Import Technology* and *Conscript All Scientists*. Squares, circles, and triangles denote CEM, PSM, and KBAL; horizontal bars are 90% confidence intervals.

For *Import Technology*, coefficients are negative in the civilian panels. CEM delivers the most precise effects, around -0.17 to -0.23; PSM and KBAL are smaller and often statistically uncertain but generally share the negative sign. In the military panels, *Military None* remains negative under CEM and PSM, while KBAL is closer to zero. When matching on exposure (*Military Exposed*), the effect is again modestly negative (about -0.10 to -0.18).

For *Conscript All Scientists*, estimates are generally positive, though not every estimator in every panel is above zero. Effects from Economic exposure and Family exposure are small ($\approx +0.08$ to $+0.20$). Effects of active military service are larger: *Military None* is roughly $+0.4$ to $+0.6$, and *Military Exposed* is of a similar magnitude. Uncertainty is greater

in the military samples, but the positive pattern is broad rather than confined to a single estimator.

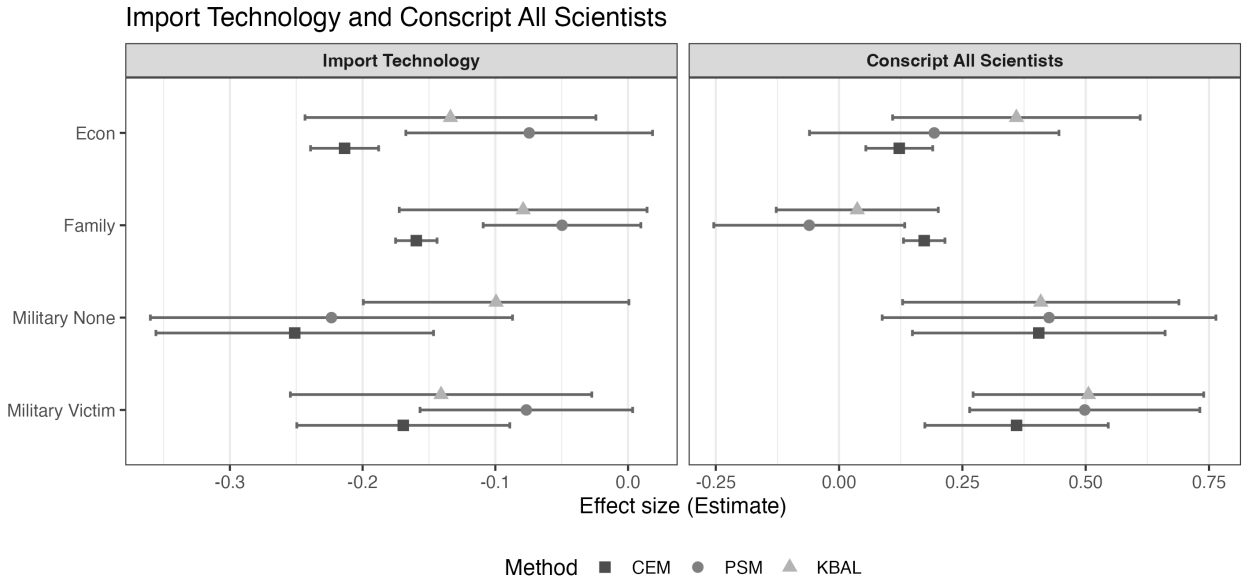


Figure 6: ATT estimates for *Import Technology* (left) and *Conscript All Scientists* (right) across Econ, Family, MilitaryâNone, and MilitaryâExposed samples. Points denote CEM (square), PSM (circle), and KBAL (triangle); bars are 90% CIs. Importing shows small to moderate negative effects, strongest and most precise under CEM. Conscription shows generally positive effects, largest in the military samples.

4.2 Considerations Behind Reliance of Domestic innovation

Various known theoretical considerations may influence a country's decision to develop technological capabilities domestically or purchase existing technologies from abroad. To investigate whether war exposure systematically influences these considerations, we asked respondents to select the most important reason guiding their preference from the following options:

> *Purchasing technology is less risky than developing our own; Building domestic technological capacity will help the economy grow;Purchasing technology from abroad is faster; Building domestic technology is better from a strategic point of view*

Those options reflect important factors behind the choice: option A speaks to the riskiness of domestic technological development; option B underscores the role of positive

spillovers from domestic technological development; option C reflects the lag behind developing technology from scratch; option D speaks to the literature highlighting international relations drivers of technological change.

Figure 7 shows average treatment effects on the treated (ATT) for four stated motives: *Faster Acquisition*, *Less Spillovers*, *Strategic Considerations*, and *Less Risky*. Positive values indicate a greater propensity to cite the motive. Dots are CEM, PSM, and KBAL estimates; bars are 90% confidence intervals. The left panel uses the economic-exposure indicator (home destroyed or forced to flee). The second panel uses the family-exposure indicator (family member killed, injured, or currently serving in the military). The third and fourth panels report the outcomes for conscripts on military duty.

Among the civilian panels, *Less Spillovers* increases in both cases. *Strategic Considerations* is essentially zero for Economic exposure and mixed, with wide intervals, for Family exposure. *Less Risky* is close to zero in the economic panel and slightly negative in the family panel. All effects are small in magnitude (within ± 0.15). Overall, exposure modestly heightens concern about domestic spillovers while leaving other stated motives largely unchanged relative to the control group.

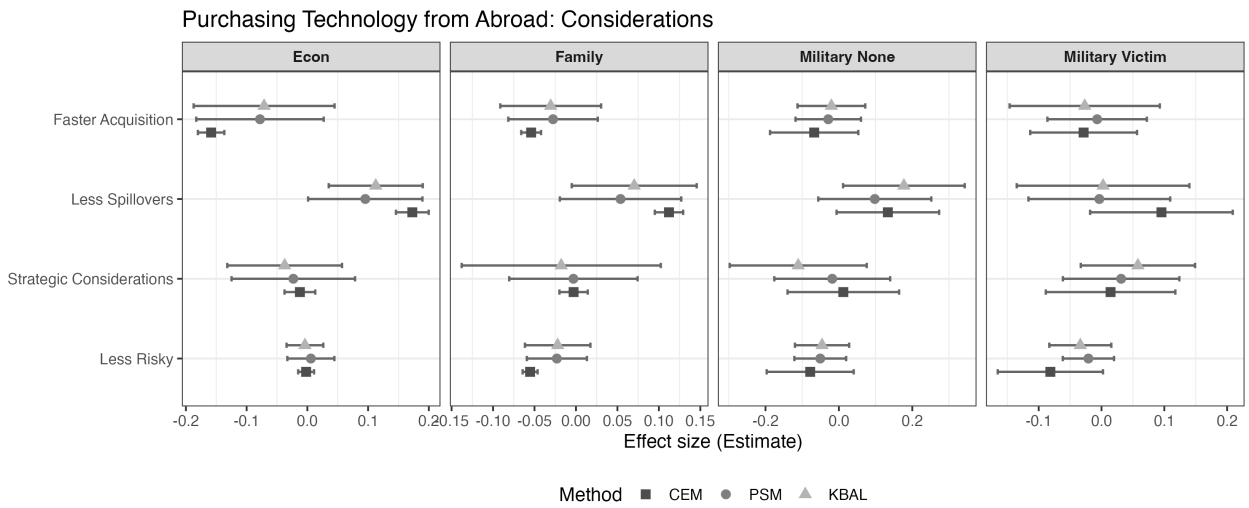


Figure 7: Purchasing technology from abroad: considerations. Points are ATT estimates from CEM (square), PSM (circle), and KBAL (triangle); bars are 90% CIs. Panel (a): economic exposure (home destroyed or forced to flee). Panel (b): family exposure (family member killed, injured, or currently serving in the military). Panels (c)–(d): military sample—Military None (service members vs. unharmed civilians) and Military Exposed (matched on other exposure). Effects are small; only *Less Spillovers* shows a consistent positive shift.

Exposure to highly technological warfare could plausibly shift these attitudes in different directions. This shift alone could explain the willingness of the government to invest in R&D. For some, Ukraine's dependence on foreign technology during wartimeâsuch as drones, missile defense systems, and satellite communications - highlights the benefits of technological reliance. Conversely, the destructive use of technology during warfare might trigger skepticism and cautious attitudes toward technological dependence, potentially reshaping opinions about technology's role in national development.

5 Robustness and Discussion

Our baseline estimates rely on matched comparisons between exposed respondents and observationally similar controls, with exact matching constraints and rich pre-treatment covariates. To assess how sensitive the central findings are to residual selection on unobservables, we complement balance diagnostics with two standard sensitivity analyses.

Coefficient stability (Oster bounds). First, we apply the coefficient-stability approach of Oster (2019). The logic is to use the movement in the treatment coefficient and the R^2 when moving from a restricted specification (with minimal controls) to a rich specification (with the full set of pre-treatment controls) to bound the treatment effect under assumptions about selection on unobservables relative to observables. Appendix Table F.1 reports the restricted and full estimates, the corresponding R^2 values, and Oster-implied bounds using the conservative benchmark $R_{\max} = 1.3\tilde{R}$ and $\delta = 1$ (equal selection on observables and unobservables). For the main outcome, *Invest in Technology*, the bounded estimates remain positive for both economic and family exposure across matching specifications, indicating that the qualitative conclusion does not hinge on modest departures from selection-on-observables. Across the full set of models in Appendix Table F.1, the bounded effect preserves the sign of the baseline estimate in all but one case (Family exposure under kernel balancing for *Import Technology*).

Rosenbaum bounds for matched designs. Second, we conduct Rosenbaum sensitivity analysis for matched samples (Rosenbaum, 2002). The results are presented in Table G.1. Rosenbaum bounds quantify how large hidden bias from an unobserved confounder would need to be to overturn inference in a matched comparison. The key parameter Γ measures the maximum ratio by which two matched units may differ in the odds of treatment because of unobservables; for example, $\Gamma = 1.2$ means that even within a matched pair, one unit could be up to 20% more likely to be treated due to unobserved factors. Appendix Table G.1 reports upper-bound p-values for a grid of Γ values. For *Invest in Technology*, the economic- and family-exposure estimates remain statistically distinguishable from zero up to approximately $\Gamma \approx 1.2$–1.3 (depending on the matching specification), implying that an unobserved confounder would need to generate on the order of a 20–30% within-pair shift in treatment odds to eliminate statistical significance. For several secondary outcomes (e.g., *Import Technology*), the sensitivity thresholds are comparable or stronger. While no observational strategy can fully rule out all unobserved confounding, the combined evidence from balance diagnostics, coefficient-stability bounds, and Rosenbaum sensitivity analysis supports the interpretation that the main patterns are not driven by small or mechanically plausible residual bias. Our analysis for civilian sample is based

on respondents residing in Ukrainian-controlled territories, potentially introducing significant selection bias favoring individuals capable and willing to leave areas that later came under Russian occupation. For our civilian sample, we confirm that the probability density of census weights in the whole sample overlaps almost perfectly with that in the matched samples (Figure 2).

5.1 Mechanisms and interpretation

First, we explore whether the shift in budget-allocation preferences comes from changes in attitudes toward technology itself.

We measure general attitudes toward technology and its role in society using questions from the World Value Survey. Respondents indicate their level of agreement with the following statements on a 5-point Likert Scale:

> *1. Because of science and technology, there will be more opportunities in life;2. Science and technology are making our lives healthier, easier, and more comfortable; 3. We are too dependent on science and technology; they are making our lives worse, not better.*

To summarize these responses into a single coherent measure, we use Principal Component Analysis (PCA). The first principal component accounts for approximately 70% of the total variation across responses and thus serves as our primary index, labeled *"Attitudes toward Technology"*.

Figure 8 summarizes average treatment effects on the treated (ATT) for the *Attitudes toward Technology* index across four samples: Economic exposure, Family exposure, Military with no reported exposure, and Military matched to reported exposure. Points denote estimates from Coarsened Exact Matching (CEM), Propensity Score Matching (PSM), and Kernel Balancing (KBAL); horizontal bars are 90% confidence intervals.

Across the civilian Econ and Family exposure, all three estimators yield coefficients clustered tightly around zero, and the confidence intervals straddle zero. These results indicate no detectable shift in average attitudes toward technology. Effects of military conscription are also clustered around zero across methods, with larger confidence intervals. The absence of detectable effects on general technology attitudes is informative:

combined with the sizable reallocations toward R&D within the fixed-sum budget task, it suggests that exposure primarily shifts perceived policy priorities and the perceived role of government in building technological capacity, rather than changing broad cultural attitudes toward science and technology.

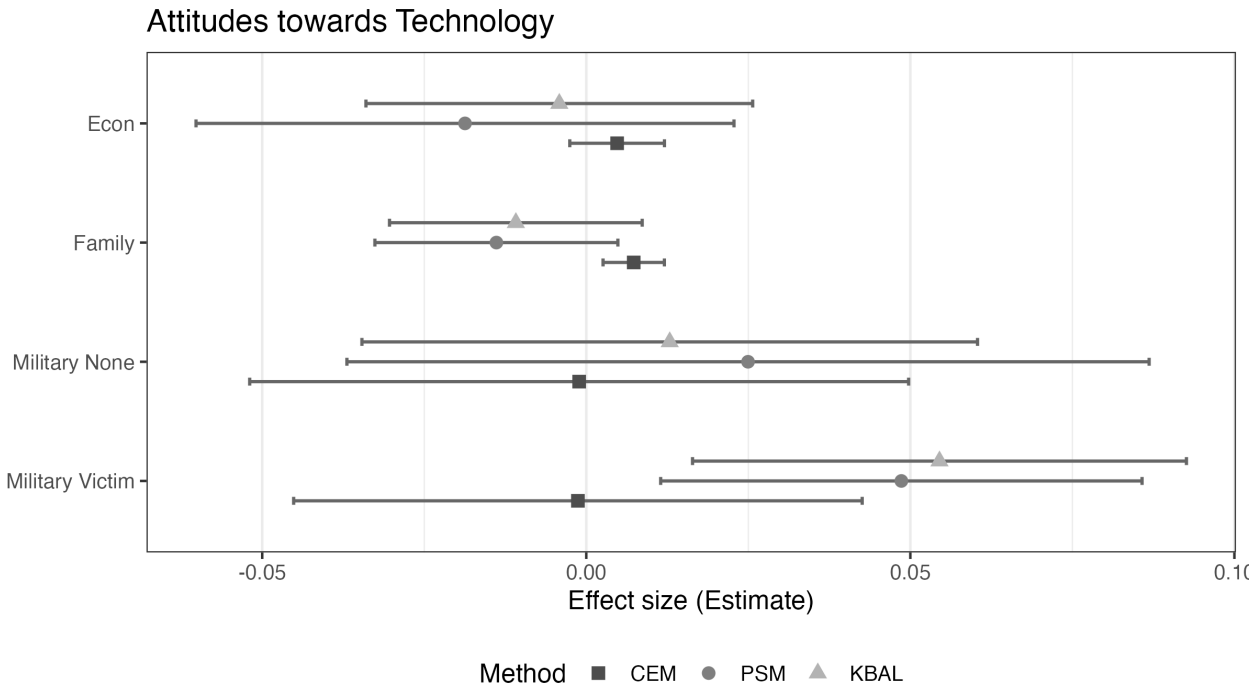


Figure 8: Average treatment effects (ATT) for the *Attitudes toward Technology* index (the first principal component of the three technology-attitude items), estimated by CEM (square), PSM (circle), and KBAL (triangle). Bars denote 90% confidence intervals. Coefficients lie close to zero in all samples; where intervals are wide, they encompass zero. The evidence is consistent with substantively null effects on broad technology attitudes.

Our central claim is not simply that exposure raises "pro-technology" preferences over budget allocation, but that it changes *how* respondents prioritize technology as a strategic component of wartime recovery—including which budget items are crowded out, which R&D domains are favored, and how respondents think about foreign procurement versus domestic mobilization. We triangulate these channels using three complementary objects: (i) levels and trade-offs in fixed-sum budget allocations, (ii) simplex-respecting compositional tests using ILR coordinates, and (iii) mechanism outcomes that capture preferences over import substitution and scientific mobilization. Throughout, we compare main estimates across matching approaches (CEM, nearest-neighbor PSM, and KBAL). The main

patterns are stable in sign across methods; differences are primarily in precision.

Figure 4 shows that individuals with greater exposure to war (be it family exposure, economic exposure, or conscription) favor greater investment in technology overall. Here we briefly unpack where the technology increase comes from. Fixed-sum budgets show the financing margins. The recovery budget allocation (Figure 9) reveals the opportunity costs implied by a higher technology priority. For civilians, Economic exposure increases the New Technology share by about $+3$ percentage points (pp), accompanied by an increase in Education of about $+2$ pp and financed primarily through a reduction in Healthcare of about -5 pp (with smaller shifts in Infrastructure and Reduce Taxes). Family exposure also increases New Technology—around $+4$ pp—but the financing margin is concentrated in Infrastructure (roughly -2 to -3 pp), with other components moving comparatively little. In the military sample, point estimates are larger and less precise, but the same qualitative feature emerges: technology increases are not "add-ons"; they come from reallocations within a fixed portfolio of recovery priorities. Notably, people who lost a home are less likely to sacrifice infrastructure, and people who have a family member killed, injured, or currently serving in the army are less likely to sacrifice healthcare.

Because budget shares lie on a simplex, we also implement joint (composition-level) inference using ILR coordinates (Figure 10). The bottom coordinate in this figure is explicitly *New Technology vs rest*, and it shifts positively for every exposure type, with civilian effects around 0.3 to 0.35 ILR units and larger shifts in the military sample. On the log-ratio scale, a change of this magnitude corresponds to a sizeable increase in the *relative* weight on technology. The remaining ILR balances clarify how the non-technology remainder is reshuffled: Economic exposure is associated with a negative healthcare balance (Healthcare vs {Infrastructure, Education, Reduce Taxes}), consistent with healthcare being an important financing margin; in the military sample, Education vs Reduce Taxes moves strongly positive, consistent with reallocations away from tax relief toward human capital. These patterns confirm that the technology shift appears as a coherent movement in composition space, rather than as five separate component-by-component comparisons.

Consistency across matching methods and exposure types. Across figures, the core comparative statics are stable across CEM/PSM/KBAL: exposure increases technology

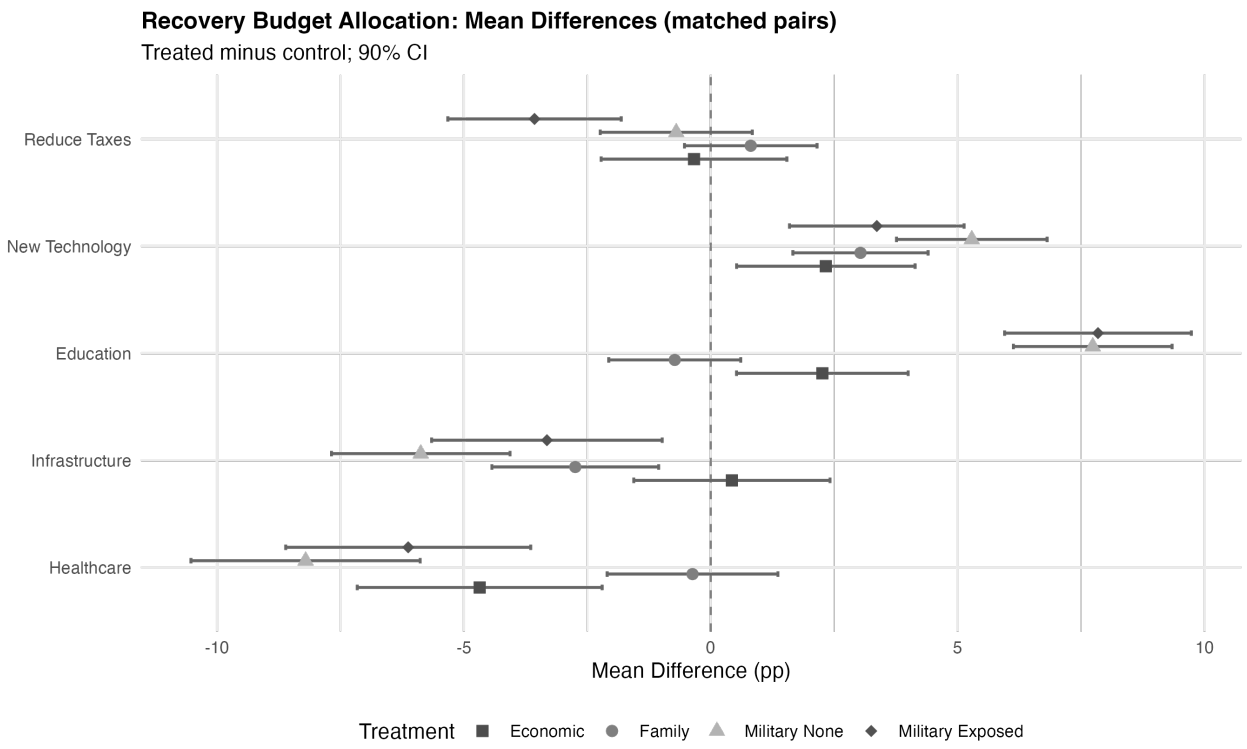


Figure 9: Recovery budget allocation: matched-pairs mean differences (treated minus control) in percentage points with confidence intervals.

investment and increases the relative weight placed on technology in the recovery portfolio (Figures 4, 9–10), while reducing support for importing technology and increasing support for domestic mobilization (Figure 6). Where methods diverge (e.g., Family exposure on conscription, Economic exposure on "faster acquisition"), divergence coincides with wide intervals and is not central to the paper's main conclusions. The exposure gradient is also coherent: effects are typically smallest for Economic exposure, larger for Family exposure, and largest for direct military exposure on the main technology-investment outcomes and mobilization preferences.

Next, we examine whether the paper's R&D preference patterns could be driven primarily by broad attitudes about continuing the war ("war fatigue/support for war"). The analysis uses an auxiliary item asked in a KIIS module that can be merged to the civilian sample; the analogous item is not available in the military module, so all results focus on civilians.

Survey item used for this analysis asks respondents to choose between (i) achiev-

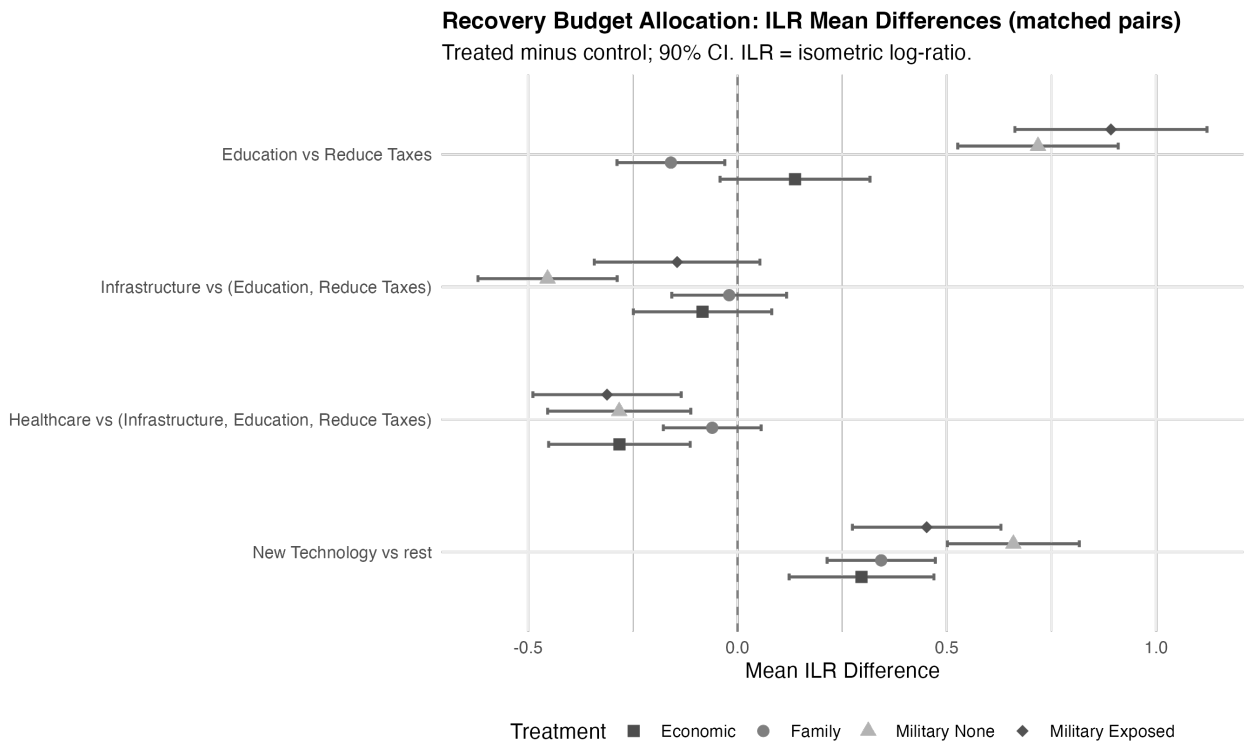


Figure 10: Recovery budget allocation in ILR coordinates: matched-pairs mean differences (treated minus control) with confidence intervals. The bottom coordinate is *New Technology vs rest*.

ing peace as quickly as possible (potentially involving territorial concessions) and (ii) never giving up any territory even if the war continues.[3] We code a binary indicator $\text{WarSupport}_i = 1$ for the "no territorial concessions" option and $\text{WarSupport}_i = 0$ for the "peace as quickly as possible" option.

War-support attitudes are plausibly affected by wartime exposure(economic hardship, family injury/death), so support for war is a post-treatment variable with respect to the exposures studied in the main text. Conditioning on such a variable can introduce post-treatment bias (Rosenbaum, 1984). For that reason, we do *not* include WarSupport_i as a control in the main analysis, and we interpret the results below as descriptive diagnostics rather than causal mediation evidence.

Using the same propensity-score matching design as in the main analysis (Rosenbaum and Rubin, 1983; Stuart, 2010), we estimate treatment-specific propensity scores for expo-

[3]The original instrument also includes "difficult to say" and refusal options; we exclude these non-substantive responses in this diagnostic.

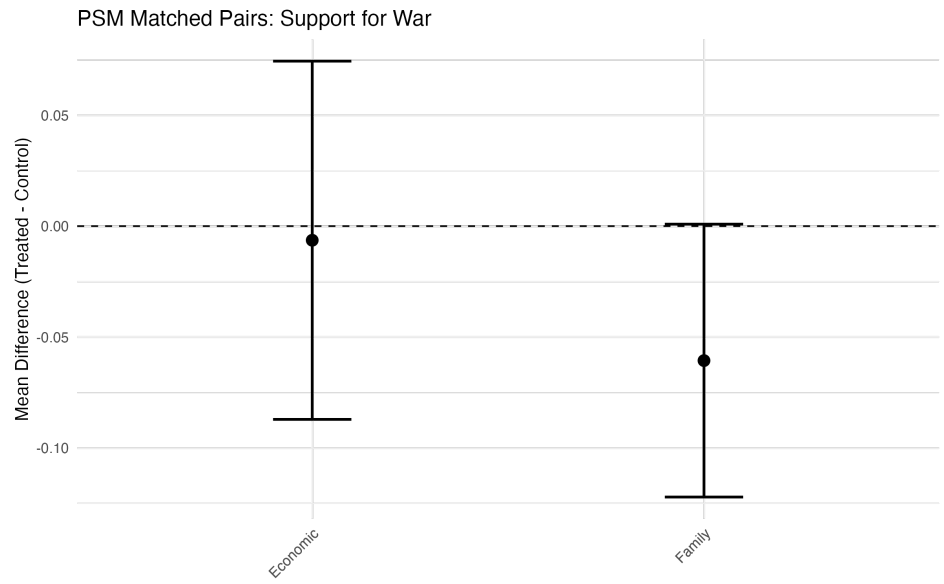
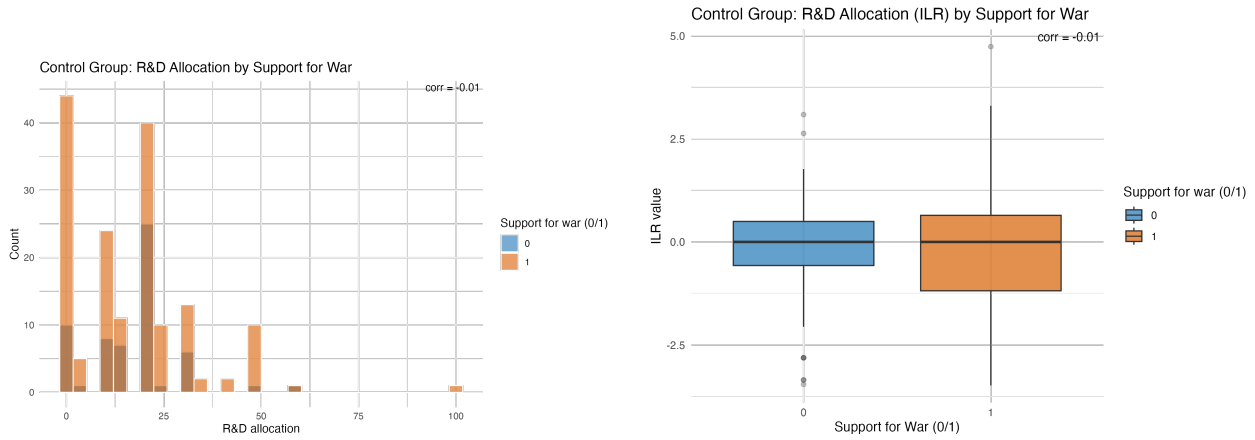


Figure 11: **War support by exposure status in matched pairs (civilians).** Points show the mean treated–control difference in WarSupport$_i$ within matched pairs (treated minus control), separately for economic and family exposure. Error bars report the corresponding uncertainty interval computed from the dispersion of within-pair differences.

sure (economic exposure and family exposure) as functions of pre-treatment covariates (settlement type, gender, age, and occupation), implement nearest-neighbor matching with replacement, and form treated–control matched pairs. For each exposure, we compute the mean within-pair difference in WarSupport$_i$ (treated minus control). Figure 11 plots these mean differences with standard-error-based uncertainty intervals.

To evaluate whether war support is likely to drive R&D preferences, we examine the relationship between WarSupport$_i$ and the R&D component of the budget allocation task among the unexposed control group only. Restricting attention to controls avoids mechanically mixing the direct effects of exposure with attitudes that may themselves be shaped by exposure.

Figure 12 shows two complementary views: panel (a) plots the distribution of the raw R&D allocation (in units out of 100), and panel (b) plots a simplex-respecting compositional summary using the isometric log-ratio (ILR) coordinate that compares the R&D component to the geometric mean of the remaining budget components. Across both panels, the distributions overlap substantially between WarSupport $= 0$ and WarSupport $= 1$, suggesting that war-support attitudes are at most weakly associated with R&D allocations



(a) Raw R&D allocation (V262)

(b) Compositional ILR: R&D vs others

Figure 12: **R&D allocations by war support in the unexposed control group (civilians).** Panel (a) shows the distribution of the raw R&D allocation (V262). Panel (b) shows the corresponding ILR coordinate comparing the R&D share to the geometric mean of the remaining budget shares. These plots are restricted to unexposed controls to keep the exercise descriptive rather than post-treatment.

in the control group.

Two patterns emerge. First, exposure to wartime hardship is associated with modest shifts in the A1 war-support proxy in matched pairs (Figure 11), consistent with the idea that exposure correlates with attitudes about war continuation. Second, within the unexposed control group, R&D allocations look similar across A1 responses (Figure 12). Taken together, these descriptive diagnostics suggest that the paper's main R&D preference results are unlikely to be mechanically driven by general war-support attitudes as proxied by A1. Because A1 is post-treatment, we treat this section as a robustness-style check rather than a causal decomposition.

6 Conclusion

Our study contributes to understanding the complex interplay between war, innovation, and public policy by leveraging unique empirical data from wartime Ukraine. We provide evidence that personal experiences of war exposure significantly influence citizens' preferences toward technological innovation and policy. Our findings indicate a clear preference among more exposed individuals for greater domestic technological in-

vestment, driven by expectations of positive economic spillovers rather than changes in risk tolerance or geopolitical considerations. Importantly, these shifts do not reflect a general ”rally-around-the-flag” rise in pro-government sentiment or a change in optimism about technology itself. Rather, they reveal a reframing of the social contract: citizens exposed to war come to view technological investment as a public good central to collective recovery and security. This insight connects literatures on state capacity, innovation, and conflict by showing that war not only destroys productive potential but can also generate the political will to rebuild it through technology.

Moreover, we identify nuanced distinctions based on the type of exposure experienced. In the civilian sample, exposure is associated with stronger support for military technology, but the broader pattern is not a uniform shift away from civilian technologies. Family exposure additionally raises support for healthcare-related innovation and lowers support for manufacturing, while military exposure shifts preferences toward healthcare and, in some specifications, basic research. Conscripts themselves do not show stronger preferences for additional military R&D.

References

Abadie, A. and Gardeazabal, J. (2003). The Economic Costs of Conflict: A Case Study of the Basque Country. *American Economic Review*, 93(1):113–132.

Abadie, A. and Imbens, G. W. (2006). Large sample properties of matching estimators for average treatment effects. *Econometrica*, 74(1):235–267.

Abramenko, S., Korovkin, V., and Makarin, A. (2024). Social media as an identity barometer: Evidence from the Russia-Ukraine war. In *AEA Papers and Proceedings*, volume 114, pages 70–74. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Abramovitz, M. (1986). Catching up, forging ahead, and falling behind. *The journal of economic history*, 46(2):385–406.

Acemoglu, D. and Robinson, J. A. (2001). A Theory of Political Transitions. *American Economic Review*, 91(4):938–963.

Aitchison, J. (1982). The statistical analysis of compositional data (with discussion). *Journal of the Royal Statistical Society: Series B (Methodological)*, 44(2):139–177.

Alesina, A., Ãzler, S., Roubini, N., and Swagel, P. (1996). Political Instability and Economic Growth. *Journal of Economic Growth*, 1(2):189–211.

Austin, P. C. (2011). An introduction to propensity score methods for reducing the effects of confounding in observational studies. *Multivariate Behavioral Research*, 46(3):399–424.

Bank, S. A. and Thorndike, J. J. (2008). *War and Taxes*. Urban Institute Press, Washington, DC.

Barro, R. J. (1991). Economic Growth in a Cross Section of Countries. *Quarterly Journal of Economics*, 106(2):407–443.

Besley, T. and Persson, T. (2009). The origins of state capacity: Property rights, taxation, and politics. *American Economic Review*, 99(4):1218–1244.

Bezvershenko, Y., Ganguli, I., Talavera, O., and Gorodnichenko, Y. (2025). Innovation for economic resilience: Strengthening Ukraine's human capital and science sector.

Biasi, B., Dahl, M. S., and Moser, P. (2021). Career Effects of Mental Health. Series: Working Paper Series Type: Working Paper.

Black, B., Lalkiya, P., and Lerner, J. (2022). The Trouble with Coarsened Exact Matching.

Boiko, I. (2019). Technological reconstruction of the global economy. *Globalization*, pages 2–22.

Branham, J. A. and Jessee, S. A. (2017). Public opinion and the american welfare state. *Political Research Quarterly*, 70(1):155–168.

Burstein, P. (2003). The impact of public opinion on public policy: A review and an agenda. *Political Research Quarterly*, 56(1):29–40.

Cabinet of Ministers of Ukraine (2022). Procedure for Organising and Maintaining Military Registration of Conscripts, Persons Liable for Military Service and Reservists (Resolution No. 1487, 30 Dec 2022).

Callen, M., Isaqzadeh, M., Long, J. D., and Sprenger, C. (2014). Violence and Risk Preference: Experimental Evidence from Afghanistan. *American Economic Review*, 104(1):123–148.

Chen, A. and Moser, P. (2024). Shell Shock: How Exposure to Combat Affected American Scientists After WWII.

Comin, D. and Hobijn, B. (2011). Technology diffusion and postwar growth. *NBER macroeconomics annual*, 25(1):209–246.

Cook, L. D. (2014). Violence and economic activity: evidence from African American patents, 1870â1940. *Journal of Economic Growth*, 19:221–257.

Cronin-Furman, K. and Lake, M. (2018). Ethics abroad: Fieldwork in fragile and violent contexts. *PS: Political Science & Politics*, 51(3):607–614.

Crump, R. K., Hotz, V. J., Imbens, G. W., and Mitnik, O. A. (2009). Dealing with limited overlap in estimation of average treatment effects. *Biometrika*, 96(1):187–199.

Dill, J., Howlett, M., and Müller-Crepon, C. (2023). At any cost: How ukrainians think about self-defense against russia. *American Journal of Political Science*.

Dyevre, A. (2023). Public R&D Spillovers and Productivity Growth.

Egozcue, J. J., Pawlowsky-Glahn, V., Mateu-Figueras, G., and Barceló-Vidal, C. (2003). Isometric logratio transformations for compositional data analysis. *Mathematical Geology*, 35(3):279–300.

Fieldhouse, A. J. and Mertens, K. (2023). The Returns to Government R&D: Evidence from U.S. Appropriations Shocks. *Federal Reserve Bank of Dallas*.

for Economic Co-operation, O. and Development (2022). Building back a better innovation ecosystem in ukraine. Policy brief, OECD. Accessed 2025-10-29.

Gross, D. P. and Sampat, B. N. (2023). America, Jump-Started: World War II R&D and the Takeoff of the US Innovation System. *American Economic Review*, 113(12):3323–3356.

Guiso, L., Sapienza, P., and Zingales, L. (2009). Cultural Biases in Economic Exchange? *Quarterly Journal of Economics*, 124(3):1095–1131.

Harhoff, D., Narin, F., Scherer, F. M., and Vopel, K. (1999). Citation Frequency and the Value of Patented Inventions. *Review of Economics and Statistics*, 81(3):511–515.

Hazlett, C. (2020). Kernel balancing. *Statistica Sinica*, 30(3):1155–1189.

Ho, D. E., Imai, K., King, G., and Stuart, E. A. (2007). Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. *Political Analysis*, 15(3):199–236.

Hoch, G., Pondorfer, A., and Shkola, V. (2025). Conflict and social capital: Evidence from the Russian War against Ukraine. *Journal of Comparative Economics*, page S0147596725000083.

Hotelling, H. (1931). The generalization of student's ratio. *Annals of Mathematical Statistics*, 2(3):360–378.

Iacus, S. M., King, G., and Porro, G. (2012). Causal Inference without Balance Checking: Coarsened Exact Matching. *Political Analysis*, 20(1):1–24.

International, A. (2023). Ukraine 2023 Human Rights Report. Technical report.

Kennedy, A. B. (2020). Technonationalism and Emerging Technologies in Israel and Taiwan. *RSIS Policy Report*.

Kibris, A. and Uler, N. (2023). The Impact of Exposure to Armed Conflict on Risk and Ambiguity Attitudes. *SSRN Electronic Journal*.

Lax, J. R. and Phillips, J. H. (2012). The democratic deficit in the states. *American Journal of Political Science*, 56(1):148–166.

Lerner, J. S. and Keltner, D. (2001). Fear, Anger, and Risk. *Journal of Personality and Social Psychology*, 81(1):146–159.

Luo, Y. (2022). Illusions of techno-nationalism. *Journal of International Business Studies*, 53(3):550–567.

Mauro, P. (1995). Corruption and Growth. *Quarterly Journal of Economics*, 110(3):681–712.

Moya, A. (2018). Violence, Psychological Trauma, and Risk Attitudes: Evidence from Victims of Violence in Colombia. *Journal of Development Economics*, 131:15–27.

Odagiri, H. (1996). The Post-War Technological Progress and Government Policies. In Odagiri, H. and Goto, A., editors, *Technology and Industrial Development in Japan: Building Capabilities by Learning, Innovation, and Public Policy*, pages 45–68. Oxford University Press.

OHCHR (2023). Ukraine: Civilian Casualties and Human Rights Violations. Technical report.

Oster, E. (2019). Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business & Economic Statistics*, 37(2):187–204.

Petrenko, R. (2024). Ratio of ukrainian volunteer soldiers to conscripts is 1 to 3 – ukraine's ministry of defence. *Ukrainska Pravda* (English edition). https://www.pravda.com.ua/eng/news/2024/06/12/7460404/. Accessed 2025-10-31.

Repetto, L., Cipullo, D., Pinchbeck, E., and Bietenbeck, J. (2026). Human-capital shocks and innovation: Evidence from britainâs lost generation.

Rosenbaum, P. R. (1984). The consequences of adjustment for a concomitant variable that has been affected by the treatment. *Journal of the American Statistical Association*, 79(387):516–524.

Rosenbaum, P. R. (2002). *Observational Studies*. Springer, New York, 2 edition.

Rosenbaum, P. R. and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1):41–55.

Rubin, D. B. (2008). For Objective Causal Inference, Design Trumps Analysis. *The Annals of Applied Statistics*, 2(3):808–840.

Ruttan, V. W. (2006). *Is War Necessary for Economic Growth? Military Procurement and Technology Development*. Oxford University Press.

Service, E. P. R. (2024). Ukrainian agriculture. Briefing, European Parliament. Accessed 2025-10-29.

Steegen, S., Tuerlinckx, F., Gelman, A., and Vanpaemel, W. (2016). Increasing transparency through a multiverse analysis. *Perspectives on Psychological Science*, 11(5):702–712.

Stuart, E. A. (2010). Matching methods for causal inference: A review and a look forward. *Statistical Science*, 25(1):1–21.

Suchikova, Y., Tsybuliak, N., Lopatina, H., Shevchenko, L., and Popov, A. I. (2023). Science in times of crisis: How does the war affect the efficiency of Ukrainian scientists? Publisher: Business Perspectives.

Tilly, C. (1975). *The Formation of National States in Western Europe*. Princeton University Press, Princeton, NJ.

Tuxhorn, Kim, D. S.-P. and Kurzban, R. (2021). Moral intuitions and support for social spending. *American Political Science Review*, 115(2):530–547.

U.S. Small Business Administration, Office of Advocacy (2023). Frequently Asked Questions About Small Business. Technical report, U.S. Small Business Administration.

Verkhovna Rada of Ukraine (2024). On Amendments to Certain Legislative Acts of Ukraine on Issues of Military Service, Mobilisation and Military Registration (Law No. 3633-IX).

Voors, M. J., Nillesen, E. E. M., Verwimp, P., Bulte, E. H., Lensink, R., and Van Soest, D. P. (2012). Violent Conflict and Behavior: A Field Experiment in Burundi. *American Economic Review*, 102(2):941–964.

Watch, H. R. (2024). Ukraine Parliament Adopts Bill on Legal Status of CRSV Survivors. Technical report.

Weber, L. (2023). Weaponized Rape in Ukraine. Technical report, UNC Law.

Wlezien, C. (1995). The public as thermostat: Dynamics of preferences for spending. *American Journal of Political Science*, 39(4):981–1000.

World Bank (2022). Ict service exports (bop, current us$) — ukraine. https://data.worldbank.org/indicator/BX.GSR.CCIS.CD?locations=UA. World Development Indicators; accessed 2025-10-29.

World Bank (2024). Charges for the use of intellectual property, receipts (bop, current us$) — ukraine. https://data.worldbank.org/indicator/BX.GSR.ROYL.CD?locations=UA. World Development Indicators; accessed 2025-10-29.

World Bank (2025). Research and Development Expenditure (% of GDP) â Ukraine.

Supplementary Information

A Supplementary Information

A.1 War exposure: Principal Component Analysis

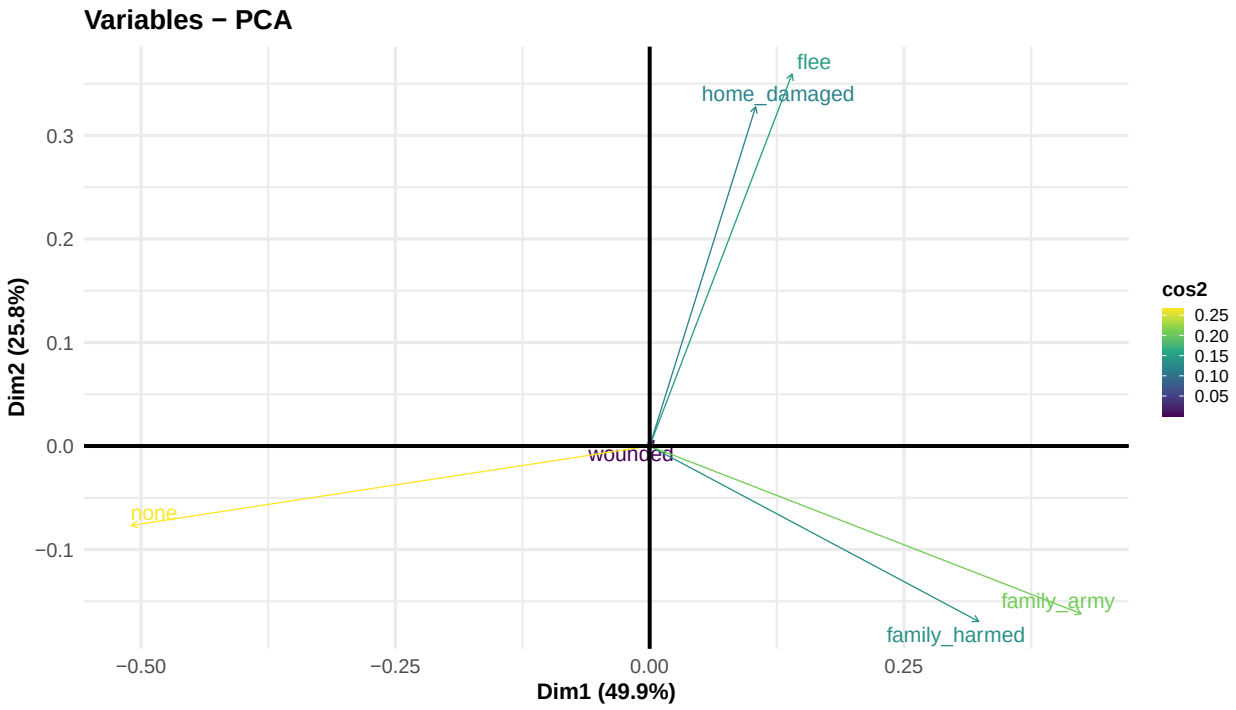


Figure A.1: Principal Component Analysis (PCA) of war exposure types

Notes: The figure visualizes the results of a PCA on reported exposure types. Arrows denote variables, with length and direction reflecting their contribution to the principal components. Small angles between arrows indicate positive correlations, large angles suggest negative correlations, and right angles (90Â°) indicate no correlation.

B Summary Statistics

Table B.1: Summary statistics

Panel A: Continuous variables

Statistic	Age	Survey weight (all2000)
Min.	18.00	0.08511
1st Qu.	39.00	0.55786
Median	54.00	0.77395
Mean	52.33	1.00264
3rd Qu.	65.00	1.16282
Max.	90.00	10.55906

Panel B: Categorical variables

Variable	Category	n	%
Economic exposure	Control	1319	67.9
	Treated	623	32.1
Family exposure	Control	717	36.9
	Treated	1225	63.1
Sex	Female	1096	56.4
	Male	846	43.6
Education	Complete higher	866	44.6
	Vocational secondary (technical school etc.)	684	35.2
	Complete general secondary (10–11 grades)	147	7.6
	Incomplete higher (3 years and more)	124	6.4
	SPTU, PTU after 10–11 grades	79	4.1
	Incomplete secondary (less than 10 grades)	23	1.2
	All other categories[a]	19	1.0
Occupation	Pension (because of age or disability)	652	33.6
	Professional (with higher education)	427	22.0
	Worker, farmworker	225	11.6
	Servant (without higher education)	148	7.6
	Householder	139	7.2
	Entrepreneur, farmer	121	6.2
	All other categories[b]	230	11.8

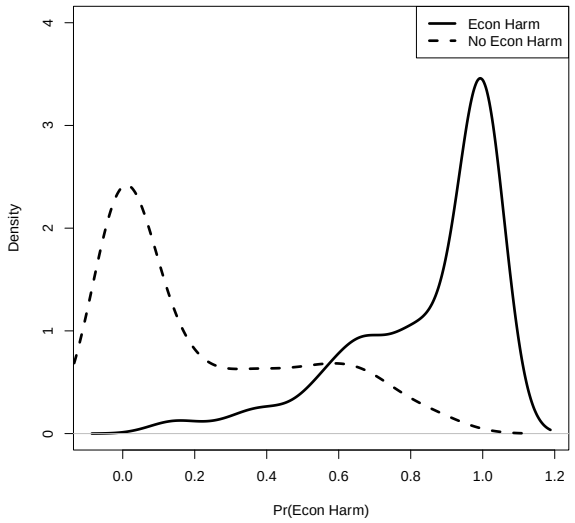
Notes: Percentages are computed out of $N = 1{,}942$

C Types of exposure in the literature

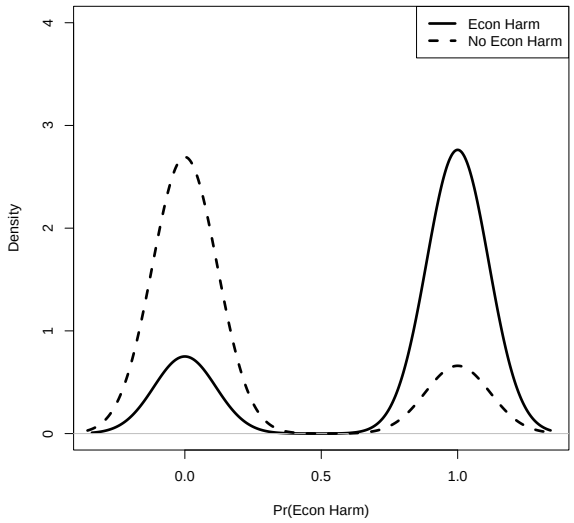
Paper	Type of exposure	exposure Measure	Outcome (Preference/Belief)
Callen et al. (2014)	Indirect (environmental) exposure	Admin data (local incidents, geocoded), fear-priming experiments	Higher risk aversion (certainty premium)
Gilligan et al. (2014)	Community-level violence	Conflict intensity in communities (quasi-random variation)	Greater social capital and cooperation
Giuliano & Spilimbergo (2024)	Indirect (ambient) war exposure (childhood)	Historical intensity (local war fatalities per capita)	Increased risk aversion and reduced trust
Kibris & Uler (2023)	Indirect (deployment in warzone) and direct trauma (combat)	Random conscription assignment, survey of combat trauma	Mixed effects: indirect (more risk tolerance), direct trauma (extreme risk aversion)
Zhukov & Talibova (2018)	Indirect (family/community historical persecution)	Archival data on Stalin-era repression	Reduced political participation
Blattman (2009)	Direct personal harm (abduction as child soldier)	Survey (former abductees vs. non-abductees)	Increased political engagement and voting
Voors et al. (2012)	Direct (personal and household) harm	Survey of personal/household war exposure	Increased risk tolerance (more risk-taking), greater local altruism
Bauer et al. (2016)	Direct personal exposure (injury, displacement)	Survey, behavioral experiments across multiple studies	Greater prosocial behavior and civic involvement
Moya (2018)	Direct personal exposure (physical harm, displacement)	Surveys measuring severity and recency of violence	Higher risk aversion (financial decisions)
Hazlett (2020)	Direct personal harm (injury)	Natural experiment (random village targeting, refugee survey)	Increased pro-peace attitudes, reduced revenge-seeking

Table C.1: Summary of Literature on Conflict exposure and Preferences

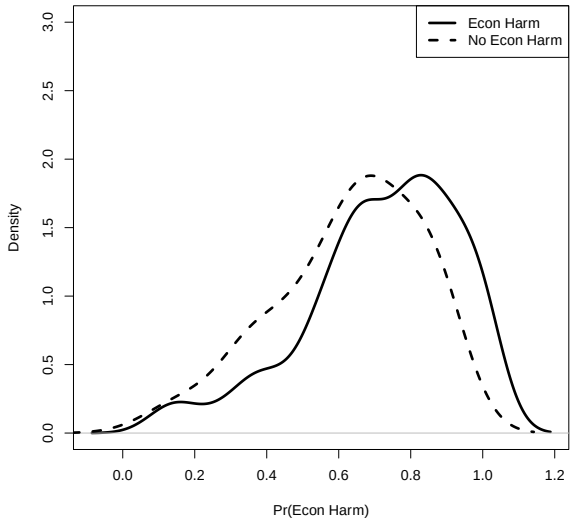
D Propensity Score Distributions: Unweighted and Reweighted (Economic Treatment)



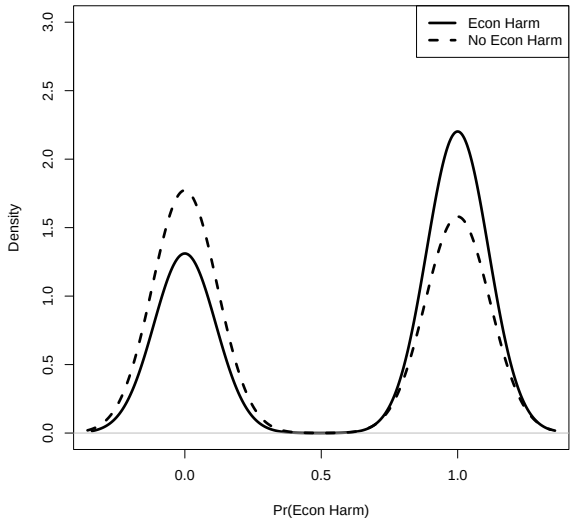
(a) Unweighted Male Economic Treatment



(b) Unweighted Female Economic Treatment



(c) Reweighted Male Economic Treatment



(d) Reweighted Female Economic Treatment

Figure D.1: Propensity Score Distributions: Unweighted and Reweighted (Economic Treatment)

Notes: Propensity scores distributions for the Econ Harm. Top panel - Without controlling for settlement, the propensity score model differentiates individuals likely to experience economic harm from those who are not based on their covariates. Bottom panel - after weighting the data, harmed and unharmed individuals have the more similar propensity score distributions

E Balance tables for Civilian Sample

Table E.1: Covariate Balance P-values by Model and Exposure Type

		Chi-squared p-values			t-test p-values	
Model	exposure	female	occupation	nationality	age	Census weights
PSM	Economic	0.339	0.712	0.379	0.072	0.743
PSM	Family	0.204	0.813	0.261	0.667	0.730
CEM	Economic	1.000	1.000	0.003	0.979	0.002
CEM	Family	1.000	1.000	0.000	0.726	0.001

F Oster Bounds

To assess sensitivity to residual omitted-variable bias, we apply the coefficient-stability approach of Oster (2019). For each outcome and matching approach, we estimate (i) a *restricted* regression including only the treatment indicator, yielding $(\hat{\beta}^R, R^2_R)$, and (ii) a *full* regression that additionally includes the full set of pre-treatment covariates used in the matching stage, yielding $(\hat{\beta}^F, R^2_F)$. We then compute the implied Oster bound $\hat{\beta}^*$ under proportional selection on observables and unobservables with $\delta = 1$ and $R^2_{\max} = 1.3 \times R^2_F$ (capped at 1). Appendix Table F.1 reports $\hat{\beta}^R$, $\hat{\beta}^F$, $\hat{\beta}^*$, the corresponding R^2 values, and the analysis-sample size N for each model.

The outcomes that anchor the paper's interpretation are also the most stable under the Oster calibration. In particular, *Import Technology* and *Less Spillovers* are extremely robust: across exposures and across CEM/PSM/KBAL, the bounded coefficients $\hat{\beta}^*$ remain very close to the full estimates $\hat{\beta}^F$ and never change sign. For *Import Technology*, full-sample coefficients range from about -0.21 to -0.08, with corresponding bounds from about -0.21 to -0.08; for *Less Spillovers*, full estimates range from about 0.07 to 0.18, with bounds from about 0.07 to 0.17 (Table F.1). This near-invariance indicates that, under $\delta = 1$, selection on unobservables of comparable strength to selection on observables would not overturn the sign or substantive magnitude of these mechanism results.

The *Invest in Technology* outcome is also robust: the Oster bound remains positive in every specification, and in most cases it is at least as large as the full estimate. For example, under CEM the Economic-exposure estimate increases from $\hat{\beta}^F = 2.97$ to $\hat{\beta}^* = 3.49$, and under KBAL from $\hat{\beta}^F = 9.01$ to $\hat{\beta}^* = 11.25$. The most conservative attenuation occurs for Economic exposure under PSM, where the bound shrinks from $\hat{\beta}^F = 0.47$ to $\hat{\beta}^* = 0.33$; importantly, even in this case the effect remains economically meaningful and does not approach zero (Table F.1). Among the substantive outcomes, this PSM–Economic case is therefore the *least* robust margin (largest attenuation), but still consistent with the our main conclusion that exposure increases support for technology investment.

The least robust outcome is the broad *Attitudes toward Technology* index: effects are small throughout, and in one case (Family exposure under CEM) the bound crosses zero ($\hat{\beta}^F = -0.0008$ vs. $\hat{\beta}^* = 0.0017$). This is substantively negligible, and it aligns with the

Table F.1: Oster (2019) coefficient-stability bounds

Model label	$\hat{\beta}_{\text{restricted}}$	$\hat{\beta}_{\text{full}}$	$\hat{\beta}_{\text{bound}}$	$R^2_{\text{restricted}}$	R^2_{full}	$R^2_{\max}$	N
Invest in Technology							
Invest in Technology (Econ - PSM)	0.931	0.472	0.333	0.001	0.128	0.166	505
Invest in Technology (Econ - CEM)	1.246	2.967	3.492	0.001	0.087	0.113	568
Invest in Technology (Econ - KBAL)	1.537	9.011	11.253	0.000	0.384	0.499	1053
Invest in Technology (Family - PSM)	1.929	1.900	1.891	0.003	0.116	0.150	917
Invest in Technology (Family - CEM)	0.847	2.768	3.346	0.001	0.121	0.158	914
Invest in Technology (Family - KBAL)	-0.122	1.697	2.243	0.000	0.414	0.538	1622
Import Technology							
Import Technology (Econ - PSM)	-0.140	-0.149	-0.152	0.023	0.181	0.236	483
Import Technology (Econ - CEM)	-0.187	-0.205	-0.213	0.048	0.169	0.220	514
Import Technology (Econ - KBAL)	-0.050	-0.119	-0.139	0.004	0.335	0.435	995
Import Technology (Family - PSM)	-0.076	-0.089	-0.093	0.008	0.128	0.167	874
Import Technology (Family - CEM)	-0.164	-0.170	-0.173	0.039	0.141	0.183	830
Import Technology (Family - KBAL)	-0.069	-0.079	-0.082	0.007	0.369	0.479	1549
Less Spillovers							
Less Spillovers (Econ - PSM)	0.078	0.095	0.100	0.005	0.156	0.203	485
Less Spillovers (Econ - CEM)	0.203	0.176	0.165	0.043	0.143	0.185	522
Less Spillovers (Econ - KBAL)	0.078	0.113	0.123	0.006	0.390	0.507	985
Less Spillovers (Family - PSM)	0.063	0.081	0.087	0.003	0.158	0.205	891
Less Spillovers (Family - CEM)	0.108	0.107	0.106	0.013	0.124	0.161	834
Less Spillovers (Family - KBAL)	0.086	0.070	0.065	0.006	0.421	0.547	1575
Attitudes toward Technology							
Attitudes toward Technology (Econ - PSM)	-0.008	-0.005	-0.004	0.001	0.122	0.159	507
Attitudes toward Technology (Econ - CEM)	-0.018	-0.045	-0.053	0.004	0.583	0.759	550
Attitudes toward Technology (Econ - KBAL)	-0.005	-0.011	-0.012	0.000	0.422	0.548	1017
Attitudes toward Technology (Family - PSM)	-0.011	-0.008	-0.007	0.001	0.101	0.131	893
Attitudes toward Technology (Family - CEM)	-0.009	-0.001	0.002	0.001	0.120	0.156	894
Attitudes toward Technology (Family - KBAL)	-0.007	-0.011	-0.012	0.000	0.467	0.607	1571

Notes: $\hat{\beta}_{\text{restricted}}$ and $R^2_{\text{restricted}}$ come from a regression with only the treatment indicator; $\hat{\beta}_{\text{full}}$ and R^2_{full} come from the corresponding regression including the full set of controls used in the matching/reweighting procedure for that method. The Oster bound $\hat{\beta}_{\text{bound}}$ is computed under proportional selection $\delta = 1$ and $R^2_{\max} = \min\{1.3 \times R^2_{\text{full}}, 1\}$. See Oster (2019).

broader pattern that exposure does not reliably shift diffuse "tech optimism" even when it shifts strategic technology-policy preferences. Notably, *23 out of 24* Oster bounds in Table F.1 preserve the sign of the full estimate; the only sign reversal is this near-zero attitudes case.

While Oster bounds are not a substitute for identification, they provide a conservative and widely used sensitivity check. In our setting, the Oster exercise strengthens the credibility of the paperâs mechanism narrative: the key policy-relevant outcomes—technology investment, lower support for importing technology, and higher concern about spillovers from foreign procurement—remain stable in sign and similar in magnitude under the $\delta = 1$ calibration (Table F.1). At the same time, the fragility of the broad attitudes index (combined with its near-zero magnitude) supports the interpretation that exposure primarily changes *strategic priorities and trade-offs*, rather than generating a blanket shift in pro-technology sentiment.

G Rosenbaum Sensitivity bounds

Sensitivity to unobserved confounding (Rosenbaum bounds). Because matching guarantees balance only on *observed* covariates, we assess how sensitive our matched-pairs conclusions are to residual selection on *unobservables* using Rosenbaum's (2002) sensitivity analysis (Rosenbaum, 2002). The framework posits that, within a matched pair, treatment assignment may still depend on an unobserved scalar $u \in [0, 1]$. The sensitivity parameter $\Gamma \geq 1$ bounds the maximal impact of this unobserved factor on treatment odds: for two matched individuals a and b, the ratio of their odds of exposure satisfies

$$\frac{1}{\Gamma} \leq \frac{\pi_a/(1-\pi_a)}{\pi_b/(1-\pi_b)} \leq \Gamma,$$

where π is the probability of exposure conditional on observed covariates and the unobserved factor. This has a particularly intuitive implication in matched pairs: if $\Gamma = 1$, exposure is as-if random within the pair ($\pi = 0.5$). If $\Gamma > 1$, the "higher-odds" unit can be exposed with probability as high as $\Gamma/(1+\Gamma)$ (and the other as low as $1/(1+\Gamma)$). Concretely, $\Gamma = 1.1$ permits at most a 0.524 vs. 0.476 split; $\Gamma = 1.2$ permits 0.545 vs. 0.455; $\Gamma = 1.3$ permits 0.565 vs. 0.435; and $\Gamma = 1.5$ permits 0.60 vs. 0.40. For each model we compute *worst-case* p-values over all hidden-bias configurations consistent with Γ in the direction of the estimated effect, and we summarize robustness via Γ^*, the smallest Γ at which the result becomes statistically insignificant at the 5% level (Appendix Table G.1).

The Rosenbaum calculations indicate that the headline effect on *Invest in Technology* is robust to *modest* hidden bias, and (in one key case) to *moderate* hidden bias. Under propensity-score nearest-neighbor matching (PSM), the Economic-exposure estimate remains significant at $\Gamma = 1.1$ (worst-case $p = 0.0127$) but becomes insignificant at $\Gamma = 1.2$ ($p = 0.0578$). An unobserved confounder would need to generate exposure-odds differences of at least about 20% within matched pairs—i.e., push within-pair assignment probabilities toward roughly 0.545 vs. 0.455—to eliminate statistical significance for this margin. The corresponding CEM specification shows a similar pattern: $p(\Gamma = 1.0) = 0.0045$, $p(1.1) = 0.0245$, and $p(1.2) = 0.0830$, so $\Gamma^* = 1.2$ as well. In contrast, the Family-exposure effect is more resilient under PSM: it remains highly significant through $\Gamma = 1.2$ ($p = 0.0087$) and only loses significance at $\Gamma = 1.3$ ($p = 0.0609$). In words, to remove statistical significance for Family–PSM *Invest in Technology*, hidden bias would need to be strong enough to allow up to a 30% difference in exposure odds within pairs (assignment probabilities as imbalanced as 0.565 vs. 0.435). The Family–CEM result is somewhat less robust: it remains significant at $\Gamma = 1.1$ ($p = 0.0378$) but not at $\Gamma = 1.2$ ($p = 0.1549$). Taken together, the investment result survives a nontrivial amount of within-pair selection on unobservables; the most robust investment margin is Family exposure under PSM ($\Gamma^* = 1.3$), while the remaining investment specifications are robust through $\Gamma \simeq 1.1$ and break around $\Gamma \simeq 1.2$.

Appendix Table G.1 also clarifies robustness across outcomes. The most robust results are those that remain significant through $\Gamma = 1.5$ (reported as $\Gamma^* > 1.5$): notably, the *Import Technology* estimates under CEM for both Economic and Family exposure, as well as *Less Spillovers* under Economic exposure (CEM). These margins would require very large

Table G.1: Rosenbaum sensitivity analysis for matched-pairs estimates

Exposure	Method	N_{pairs}	$p(\Gamma{=}1.0)$	$p(1.1)$	$p(1.2)$	$p(1.3)$	$p(1.4)$	$p(1.5)$	Γ^*
Invest in Technology									
Economic	PSM	369	0.0015	0.0127	0.0578	0.1667	0.3420	0.5454	1.2
Economic	CEM	284	0.0045	0.0245	0.0830	0.1978	0.3613	0.5417	1.2
Family	PSM	672	< 0.0001	0.0005	0.0087	0.0609	0.2180	0.4741	1.3
Family	CEM	457	0.0045	0.0378	0.1549	0.3758	0.6294	0.8245	1.2
Import Technology									
Economic	PSM	349	0.0108	0.0391	0.1012	0.2034	0.3379	0.4856	1.2
Economic	CEM	257	< 0.0001	< 0.0001	< 0.0001	0.0001	0.0005	0.0013	> 1.5
Family	PSM	643	0.0092	0.0432	0.1291	0.2760	0.4603	0.6410	1.2
Family	CEM	415	< 0.0001	< 0.0001	< 0.0001	< 0.0001	0.0001	0.0003	> 1.5
Less Spillovers									
Economic	PSM	346	0.0044	0.0217	0.0699	0.1634	0.3006	0.4613	1.2
Economic	CEM	261	< 0.0001	< 0.0001	0.0001	0.0003	0.0012	0.0038	> 1.5
Family	PSM	651	0.0225	0.1202	0.3379	0.6088	0.8211	0.9357	1.1
Family	CEM	417	0.0004	0.0030	0.0146	0.0483	0.1187	0.2307	1.4

Notes: The table reports p-values from Rosenbaumâs sensitivity analysis for matched pairs (Rosenbaum, 2002). $\Gamma \geq 1$ bounds the extent of hidden bias within matched pairs: two matched units may differ in their odds of treatment by at most a factor Γ due to an unobserved confounder. Γ^* is the smallest Γ at which the p-value exceeds 0.05; entries of > 1.5 remain significant through $\Gamma = 1.5$.

within-pair odds imbalances—on the order of a 50% difference in odds (60–40 assignment probabilities)—to be rendered insignificant under the Rosenbaum calibration. At the other extreme, the comparatively most fragile margin is *Less Spillovers* under Family exposure with PSM, which becomes insignificant already at $\Gamma = 1.1$ ($\Gamma^* = 1.1$). Most PSM results lie between these extremes, typically losing significance around $\Gamma \simeq 1.2$, indicating robustness to small hidden bias but sensitivity to larger deviations from conditional random assignment.

Rosenbaum bounds do not identify the causal effect; rather, they quantify how strong an unobserved factor would need to be—in terms of *within-pair exposure odds*—to overturn the matched-pairs inference. In our context, the bounds support the credibility of the core technology-investment result (especially for Family exposure under PSM) and indicate that the procurement/autonomy mechanism results estimated under CEM are particularly resilient, while also transparently flagging which specifications are more sensitive to potential residual selection.

H Compositional robustness checks

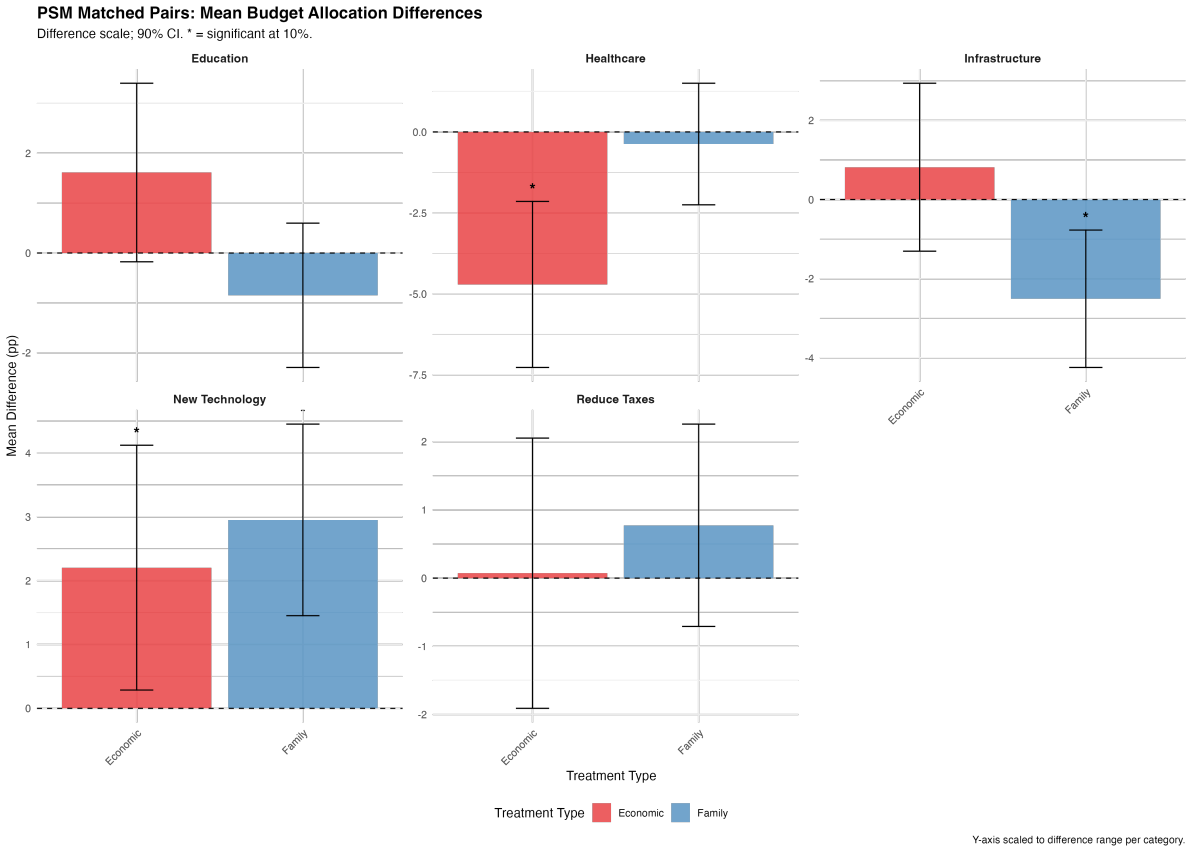
H.1 Where does R&D funding come from?

The main focus of the paper is on preferences for government investment in R&D, yet it may be of interest to see what options finance this shift. Figure H1 reports matched-pair mean differences for the five-part recovery-budget allocation (units of budget sum to 100 within respondent) for *within-pair* treated–control differences after propensity-score matching. Specifically, for each treatment we construct 1:1 matched pairs using observed covariates and then compute, for each category k, the matched-pair difference $\Delta_{ik} = y_{ik}^{(T)} - y_{ik}^{(C)}$ (in percentage points). We summarize effects by the mean of Δ_{ik} across pairs and report 90% confidence intervals based on the dispersion of the paired differences (Rosenbaum and Rubin, 1983; Stuart, 2010; Abadie and Imbens, 2006).

Several patterns emerge. First, under the *economic exposure* treatment, the largest movement is a sizable reduction in the healthcare share of the budget (roughly 4–5 percentage points), accompanied by increases in "new technology" and (to a lesser extent) education and infrastructure. Second, under the *family exposure* treatment, support for "new technology" increases (roughly 3 percentage points) while healthcare changes little; the offsetting reductions are concentrated in infrastructure (and to a lesser extent education). Taken together, these patterns are consistent with the interpretation that family exposure is associated with a shift toward new technology that is *not* financed by reducing healthcare (i.e., respondents do not "sacrifice healthcare for new technology"), whereas economic exposure does not appear to reduce the infrastructure share (if anything it is slightly higher in treated units), with the main offset coming from healthcare. These agree with the expectation that people who lost their homes are less likely to sacrifice investment in infrastructure recovery, while people whose family members were killed/injured or are currently in the army are less likely to sacrifice healthcare expenditures and serve as a sanity check for our analysis .

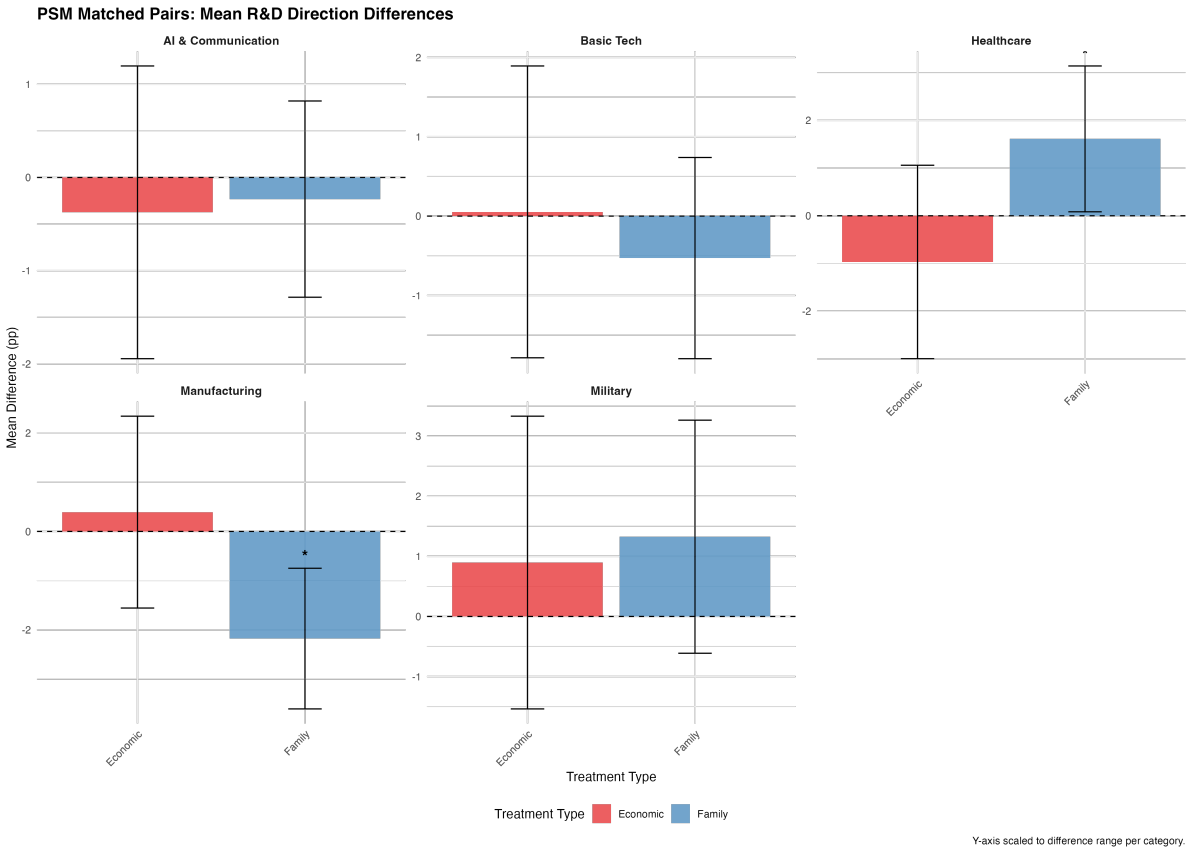
We then repeat the analysis for the R&D-allocation task, investigating preferences over

Figure H1: Matched-pair mean differences in recovery-budget shares



the direction of technological change. While both treated groups in the civilian sample favor military technology, the broader pattern is similar to the one observed for the general recovery budget: family exposure is associated with more investment in health-related technologies and less in manufacturing, while economic exposure shows smaller and less systematic shifts across the non-military categories.

Figure H2: Matched-pair mean differences in R&D-allocation/direction shares



H.2 ILR-based tests of compositional shifts in matched pairs

Budget allocations are compositional: respondents distribute 100 points across categories, so only *relative* shares are meaningful and the observations lie on the simplex (Aitchison, 1982). To respect the adding-up constraint, we re-express each allocation as proportions, apply a small replacement constant for zero shares (followed by renormalization), and use the isometric log-ratio (ilr) transformation, which maps a K-part composition to $K-1$ orthonormal coordinates in $\mathbb{R}^{K-1}$ (Egozcue et al., 2003).

We implement propensity score matching (nearest-neighbor) to form treated–control matched pairs and compute within-pair differences in ilr coordinates (treated minus matched control) (Rosenbaum and Rubin, 1983; Ho et al., 2007). For each treatment and block, we test whether the mean ilr-difference vector equals zero using Hotelling's T^2 one-sample test (Hotelling, 1931). Because individual ilr coordinates depend on the choice of or-

thonormal basis, we emphasize the joint T^2 test; coordinate-specific mean differences are reported descriptively.

Table H1 reports results for two blocks: (i) the recovery-budget allocation block and (ii) the R&D-allocation/direction block. The joint test indicates statistically significant compositional shifts in the recovery-budget block for both treatments, no evidence of a compositional shift in the R&D block under the economic treatment, and marginal evidence under the family treatment.

Table H1: Compositional shifts in budget allocations (ilr / Hotelling T^2), matched pairs

Treatment	Block	N	T^2	$F(4, N-4)$	p	Mean ilr difference $(\Delta z_1, \ldots, \Delta z_4)$
Economic	Budget: R&D	334	13.2736	3.2885	0.0116	$(-0.35, -0.13, -0.01, 0.20)$
Family	Budget: R&D	577	22.0814	5.4916	0.000 24	$(-0.15, -0.13, -0.28, 0.18)$
Economic	R&D budget: Military	339	0.2687	0.0666	0.9920	$(-0.02, -0.06, -0.01, -0.01)$
Family	R&D budget: Military	597	8.9845	2.2348	0.0640	$(0.11, 0.10, 0.15, -0.09)$

Notes: Each row reports Hotellingâs T^2 test applied to within-pair differences in ilr coordinates (treated minus matched control) for a five-part composition ($K = 5$, hence four ilr coordinates). The reported F statistic is the standard $T^2 \mapsto F$ transformation under the null of zero mean shift. Coordinate-specific means depend on the ilr basis and are not interpreted individually.

Figure H3 provides the corresponding coordinate-level plot for the recovery-budget composition. It is useful descriptively, but because individual ilr coordinates depend on the chosen orthonormal basis, the main inferential object remains the joint Hotelling's T^2 test reported in Table H1.

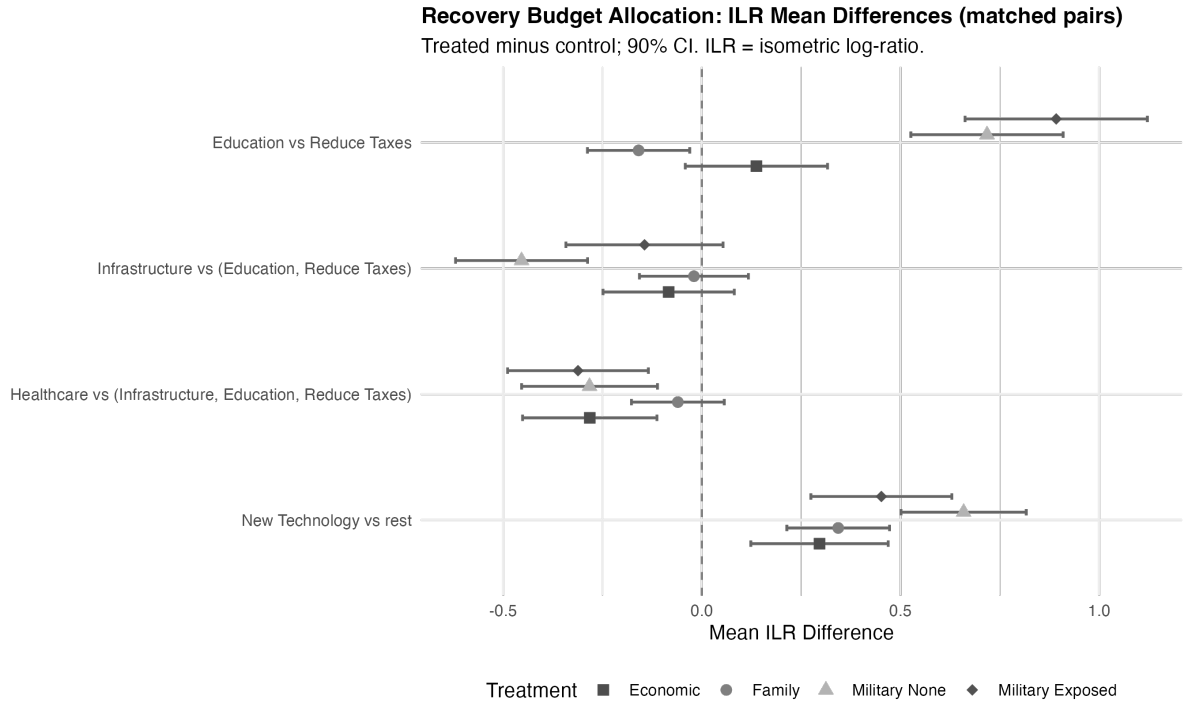
I Matched-sample coverage and common support

Table H1: Matched-sample coverage and common support

Exposure	Matching method	Treated eligible (N_T)	Treated matched (N_T^m)	Retained (%)
Economic	PSM (NN, with replacement)	623	362	58.1
Economic	CEM	623	125	20.1
Family	PSM (NN, with replacement)	1225	209–220	17.1–18.0
Family	CEM	1225	199–217	16.2–17.7

Notes. N_T counts treated respondents eligible for each outcome after applying outcome-specific filters and removing missing values. N_T^m counts treated respondents for whom a valid match exists under exact matching within pre-war settlement (common support). Because outcomes have small amounts of missingness, N_T^m varies slightly across outcomes; regression tables report the exact N used in each specification. Matching is performed with replacement; inference clusters by the matched control identifier.

Figure H3: Recovery-budget composition in ilr coordinates: matched-pair mean differences



Notes: The plotted coordinates are the orthonormal ilr balances for the five-part recovery-budget composition. The bottom coordinate compares *New Technology* to the geometric mean of the remaining categories. Positive values indicate a higher relative budget weight among treated respondents than among their matched controls. Because coordinate interpretations depend on the chosen balance basis, the figure is descriptive and the joint Hotelling's T^2 test in Table H1 remains the main inferential object.