Testing the Empirical Validity of the Work Preference Labor Supply Model: Evidence from a Guaranteed Income Program for Artists in New York State

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This study investigates the impact of the Creatives Rebuild New York (CRNY) Guaranteed Income for Artists (GIA) program on labor supply and earnings among New York State artists. The program provided 2,400 artists with $1,000 monthly, unconditional payments for 18 months to address financial instability and promote artistic practices. Using a matched comparison of participant and control group data, the analysis reveals that guaranteed income increased time spent on arts work by 3.9 hours weekly while reducing non-arts work by 2.4 hours. Although participation in arts-work grew, earnings from both arts and non-arts sectors declined, indicating a shift in financial reliance enabled by guaranteed income. The findings help validate Throsby (1994) work-preference model, emphasizing the intrinsic value of artistic labor over monetary incentives, especially nonlabor income.

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1 — Introduction

The concept of artists participating in multiple labor markets-both within and outside the arts-is rooted in Throsby's (1994) work-preference model, which departs from traditional labor supply theory by positing that labor decisions are influenced not only by income but also by the personal satisfaction derived from particular types of work. This framework is particularly well suited to understanding artistic labor, as artists have long been associated with strong intrinsic motivations that often outweigh financial considerations. In this model, artists may choose to accept lower earnings or irregular employment in the arts because of the nonpecuniary utility they derive from creative work.

Building on this foundation, Throsby (2007) further argues that the structure of artistic labor markets is distinct from other occupations in that artists often allocate their labor across multiple markets—not always in their primary artistic field—reflecting the dual pressures of earning income and pursuing meaningful work. Traditional labor supply models typically emphasize wage-based incentives, but Throsby's formulation allows for a richer understanding of why artists might persist in creative careers despite low or unstable pay.

Empirical studies have tested different aspects of the work-preference model by examining factors such as job satisfaction and time allocation between arts and non-arts work. For instance, research by Bille et al. (2013) and Steiner and Schneider (2013) find that artists report higher job satisfaction than non-artists, even after accounting for differences in income, working hours, and personality— supporting the notion that artists derive intrinsic benefits from their work. Other research has examined time allocation more directly. Robinson and Montgomery (2000) find that artists do respond to economic incentives, though often only at the margins—consistent with the "weak" version of the work-preference model. Similarly, Bille (2017) and Casacuberta and Gandelman (2012) show that non-labor income and alternative income streams can influence how artists allocate their time, further complicating any model that assumes labor is supplied solely in response to wages. Together, this literature reinforces the relevance of Throsby's model for understanding artistic labor, particularly in its emphasis on non-monetary motivations and the need to account for multiple and diverse income sources—such as royalties, grants, or part-time non-arts employment—when modeling artists' labor supply decisions.

Nevertheless, the literature is in short supply of more direct tests of Throsby's work-preference model, such as observing labor supply shifts in response to a shock to relative wages or to the subsistence income constraint. Most existing studies rely on cross-sectional survey data or correlational analyses, which offer suggestive but indirect evidence of work-preference behavior. What remains largely untested is how artists actually reallocate their labor when their financial conditions materially change—precisely the kind of behavioral shift Throsby's model predicts under relaxed income constraints. Experimental or quasi-experimental approaches, such as evaluating guaranteed income programs or other exogenous income shocks, offer more powerful means of identifying causal relationships between income and artistic labor supply. These types of studies can observe whether artists, when relieved from the necessity of earning subsistence income, choose to increase their time spent on creative work, reduce non-arts employment, or make other labor-leisure trade-offs that reflect a strong intrinsic preference for artistic labor. Such designs go beyond measuring stated preferences or static allocations and instead allow for dynamic assessments of artists' labor decisions under varying economic conditions. As a result, they provide a more rigorous empirical test of Throsby's central claim: that artists, unlike other workers, will favor creative work over higher earnings when given the financial freedom to do so.

In this study, we evaluate the labor supply outcomes of artists participating in a guaranteed income program, in effect testing whether there is empirical validity to the work-preference model. Guaranteed income refers to regular, unconditional cash transfers provided to individuals to ensure a basic level of financial security, without work requirements or restrictions on how the money is spent. Similar programs have been implemented in other regions, such as the Artist Relief Fund in San Francisco, which provided emergency stipends to artists during the pandemic (Yerba Buena Center for the Arts, n.d.), and the Saint Paul Guaranteed Income for Artists pilot, which offered $500 monthly payments to local artists to support their ongoing creative work (Springboard for the Arts, n.d.). Additionally, Ireland's Basic Income for the Arts pilot scheme provided €325 per week to 2,000 artists and creative workers over a three-year period, aiming to address financial instability in the arts sector (Department of Culture, Heritage and the Gaeltacht (Government of Ireland), n.d.). These programs, like CRNY's, aimed to provide financial stability and empower artists to continue their practice despite economic challenges.

While these initiatives are targeted specifically at artists, they share structural features with broader Universal Basic Income (UBI) schemes—namely, unconditional, regular cash transfers designed to promote economic security and individual agency. UBI has attracted attention in both economic and political theory for its potential to alleviate poverty, reduce inequality, and improve well-being without distorting labor incentives (Hoynes and Rothstein 2019; Bidadanure 2019). Artist-focused guaranteed income programs, therefore, offer a unique lens through which to study the effects of UBI-like interventions in a distinct labor market characterized by precarity, intrinsic motivation, and portfolio careers. These sector-specific pilots contribute valuable evidence to ongoing UBI debates by testing core assumptions—such as whether unconditional cash support reduces labor supply or instead enables more meaningful, self-directed work.

In this paper, we use data from a guaranteed income program for artists in New York State through Creatives Rebuild New York (CRNY). The CRNY Guaranteed Income for Artists (GIA) initiative – funded with $125 million from the Andrew W. Mellon Foundation, the Ford Foundation and the Stavros Niarchos Foundation – provided 2,400 artists with monthly, unconditional cash payments of $1,000 over 18 months, with the primary goal of alleviating financial instability among artists and supporting their creative practices. The program specifically targeted vulnerable artist populations, including those from marginalized communities and those facing systemic barriers to accessing funding opportunities.

Using application and survey data collected from both the participants in the program and a control group of unselected applicants, we present the findings of a matching procedure that balances the treatment and control groups and estimates the impact of guaranteed income on time spent on work and earnings. Our analysis found that the guaranteed income payments led to a significant increase in the time artists spent on their creative work. Artists enrolled in the program were more likely to spend time on arts- and arts-related work compared to artists in the control group. Furthermore, participants in the program reported an average increase of 3.9 hours per week dedicated to arts work. Conversely, they decreased their hours spent on non-arts work by 2.4 hours, suggesting that the guaranteed income enabled artists to prioritize their creative pursuits over other forms of employment. However, there was a concomitant reduction in annual earnings from arts-related and non-arts work, highlighting a trade-off between creative engagement and other income-generating activities. All in all, we find rich evidence that the work-preference model is an appropriate perspective for how artists make decisions about the allocation of work and that non-labor income matters in artists' choice of labor markets.

2 — Artists' Labor Supply

To appreciate the labor supply effects of an unconditional cash transfer, we develop a work-preference model that accounts for work in arts and non-arts markets and for "psychic income" from arts work (Thurow 1978; Baumol and Throsby 2012) drawing from (Throsby 1994).

We begin with a standard labor supply model where the utility of one's labor is a function of their consumption level x and leisure hours λ, the latter which is the inverse of hours worked. With total hours available for work or leisure standardized and set to 1, and consumption prices at p, the individual's optimization problem is to maximize:

$$U(x, \lambda) \quad \text{s.t.} \quad px = w(1 - \lambda) + V \tag{1}$$

The utility is subject to a budget constraint equal to the total earnings from work at wage w and any non-labor income (V). As with any labor supply model, utility is increasing in leisure and consumption, and we can assume leisure and consumption are normal goods. If we maximize the above utility function, we derive the familiar backward-bending labor supply curve shown in Figure 1. In such a general setting, increasing wages has theoretically ambiguous effects on labor supplied. In other words, raising wages can have mixed effects on how much people choose to work—it might lead some to work more and others to work less especially if demand for leisure rises quickly in income.

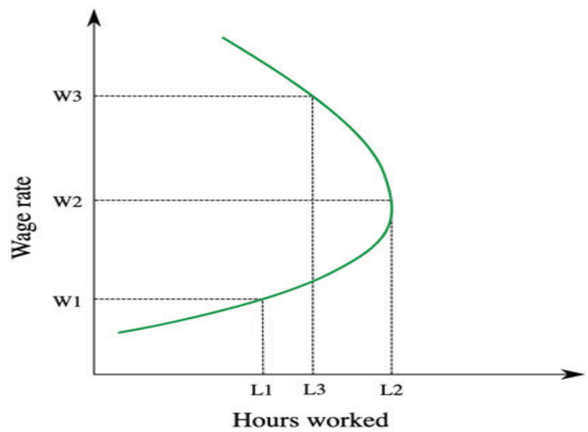

Figure 1 — Traditional Labor Supply Curve

Taking into account that artists tend to derive substantial non-pecuniary benefits, or psychic income from work, we can amend the utility equation to include both time spent working in the arts and time spent working in non-art labor markets. In other words, the utility framework now models the choice that artists make with respect to arts versus non-art work. Per Throsby (1994), we hold leisure time fixed and just consider the allocation of labor time between arts (L_a) and non-arts (L_n) markets. For wages w_a and w_n, respectively, the individual's optimization problem becomes:

$$\text{maximize } U = U(x, L_a) \quad \text{s.t.} \quad w_a L_a + w_n(1 - L_a) - px = 0 \tag{2}$$

This construction allows for psychic income or utility from L_a. As Throsby shows, artists allocate labor between arts and non-arts work in ways that might involve corner solutions (i.e., $L_a = 0$ or $L_a = 0$) or some mix of work in both markets. With a binding subsistence constraint (i.e., $\underline{x} > x^*$), a mix like this is more likely as optimal allocations will tend to have more non-arts labor supplied. The hypothesis that artists will shift from non-arts labor to arts labor as their subsistence constraint relaxes directly follows from Throsby's work-preference model. Further, his model predicts a decline in earnings as subsistence constraints relax as in Figure 2 taken directly from Throsby (1994).

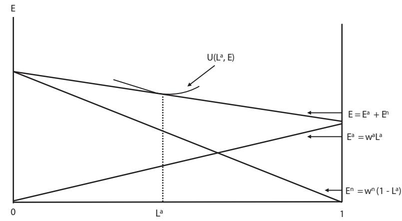

Figure 2 — Weak Version of Work Preference Model

3 — Creatives Rebuild New York (CRNY) Guaranteed Income for Artists (GIA) Program

The impact of guaranteed income programs on labor supply has been a subject of significant debate, particularly concerning their effects on work incentives. These programs are often situated within the broader framework of basic income—an economic policy proposal that involves providing all individuals with a regular, unconditional cash payment, regardless of employment status or income level. Basic income is grounded in the idea that a minimum level of financial security enables people to make choices that align more closely with their values and capacities, potentially leading to improvements in well-being, civic engagement, and labor market participation.

Empirical studies have begun to test these claims. For example, Painter and Smith (2022), examining the Alaska Permanent Fund—one of the longest-standing basic income–like programs—found that guaranteed income had minimal negative effects on labor supply while increasing overall well-being. Similarly, Jones and Marinescu (2018) analyzed the effects of the Manitoba Basic Income Experiment and concluded that while there was a slight reduction in work hours, participants experienced improved mental health and economic stability. A recent study examined the employment effects of a guaranteed income by providing 1,000 low-income individuals with $1,000 per month unconditionally for three years, compared to a control group receiving $50 per month. The findings indicated a modest reduction in labor supply, with participants working approximately 1.3 fewer hours per week, but also reported increased financial stability and well-being (Vivalt et al. 2024). These papers provide important context for understanding how guaranteed income can influence labor supply in various settings.

The Creatives Rebuild New York (CRNY) Guaranteed Income for Artists (GIA) Program provided a total of 2400 artists across New York State with monthly, no-strings-attached cash payments of $1,000 over an 18-month period. The program's goal was to alleviate financial instability among artists, particularly those facing systemic barriers, and to support their artistic practices by providing consistent income support.

3.1. Recruitment

CRNY implemented an outreach strategy to ensure that the program reached certain targeted populations deemed vulnerable with respect to receiving funding for creative work. The outreach included the hiring of a diverse Artist Outreach Corps, composed of artists from across the state who had deep ties to underrepresented communities. These outreach efforts were aimed at connecting with artists who might not typically have access to funding opportunities, such as undocumented individuals, those without bank accounts, and those living in rural areas.

A Help Desk was established to provide real-time support throughout the application process, fielding questions and assisting applicants who required additional guidance. This service was particularly valuable for artists who lacked internet access or were unfamiliar with digital application processes. As a result of these outreach and support efforts, a total of 22,620 applications were submitted.

The application process itself was designed to be simple and accessible, with minimal barriers to entry. The application was available in multiple languages and was accessible to individuals with disabilities. Applicant feedback indicated that the application was easy to complete, and the support provided throughout the process was helpful in making the program widely accessible.

3.2. *Selection and Verification*

The selection process was based on a weighted lottery system, which aimed to prioritize artists facing "multi-point oppression." This system gave preference to artists from marginalized backgrounds, including Black, Indigenous, and People of Color (BIPOC), LGBTQIAP+, deaf/disabled individuals, caregivers, and those involved with the criminal legal system. Applicants who identified with one or more prioritized identities had their names entered into the selection pool multiple times, increasing their likelihood of being chosen. The selection process used an algorithm that randomly selected participants from the pool, but those with more entries had a higher chance of being selected. The algorithm also guaranteed that at least one artist from each county in the state was chosen.

Once selected, artists were required to undergo a verification process to confirm their eligibility. This process involved submitting documentation to verify three key criteria:

- Proof of being an artist, culture-maker, or culture-bearer. CRNY aimed to use an inclusive interpretation that captured diverse artistic practices. They sought to encompass individuals whose work might not produce conventional art products, but who were deeply committed to artistic expression. They defined artist, culture bearer, or culture maker as someone engaged in artistic practice to express themselves, preserve cultural traditions, impact communities, or provide cultural resources. Artists must either have derived income from their work or contributed to community-building, with a commitment to sharing their practice. CRNY outlined various eligible disciplines, including craft, dance, music, and performance art, while excluding purely commercial work like wedding photography or culinary arts. The assessment of this criterion focused solely on eligibility, with no evaluation of artistic quality.
- Residency in New York State.
- Financial need, as determined by the Self-Sufficiency Standard (Pearce and Brooks 2000). This measure accounts for variations in the cost of living by household composition and across different geographic regions in New York in order to provide a more accurate reflection of financial need than traditional poverty measures.

CRNY partnered with Steady App (to verify financial need), Probity (to verify residency), and contracted artist reviewers (to assess artistic status) to manage the verification process. This multi-step verification ensured that the program reached artists who met the program's requirements while maintaining a fair and transparent selection process.

A total of 1,957 pre-selected applicants successfully submitted complete documentation and were approved for the program. Despite at least five follow-up attempts by CRNY, around 400 individuals did not submit any documentation. As a result, 452 applicants from the waitlist who completed the verification process were invited to enroll. Nine eligible artists chose not to join the program. Fewer than eight percent of applicants failed verification, which included a small group who misrepresented their status as artists or provided false information about their income or residency. Additionally, a minor "fraud ring" was uncovered, involving five applications that used the same fraudulent identification materials.

3.3. Payment Disbursement

After participants confirmed their decision to join the program, they began the onboarding process to establish payment connections. This process varied depending on several factors, such as whether the individual had a Social Security number, a bank account, or could connect to Steady, CRNY's payment platform. Artists were given the option to receive payments via direct deposit, which required a bank account compatible with Steady, or through a prepaid debit card provided by Community Financial Resources, designed for those who were unbanked or lacked a Social Security number. For artists whose banks or credit unions were incompatible with Steady, some had to open new accounts, with CRNY and Steady assisting in the process. 2,215 artists received payment through direct deposit via Steady, while 185 received funds via prepaid debit cards or deposits into newly formed credit union accounts through Community Financial Resources.

Table 1 — CRNY GIA Payment Cohorts and Timing

Payment Cohort	Number of Participants	First Payment Date	Final Payment Date
1	989	6/30/2022	11/15/2023
2	664	7/15/2022	12/15/2023
3	174	8/15/2022	1/15/2024
4	462	9/15/2022	2/15/2024
5	111	10/15/2022	3/15/2024

Note: *If the 15th fell on a weekend or holiday, then payment was made on the Friday before.*

As Table 1 shows, artists were admitted into the program on a rolling basis across five different cohorts, with payments beginning on June 30, 2022 and continuing through March 15, 2024. Artists opting for a debit card received their first payment on July 15. Around 100 payments initially failed in the first cohort due to bank linking issues. Steady, having only previously handled smaller cohorts, initially struggled with onboarding a group of this size. However, the issues were resolved for subsequent cohorts, and the payment failure rate dropped to below 0.2 percent per month, primarily due to updates in participants' banking information.

4 — Data

All eligible GIA applicants are included in the study. For this study, we use two types of data: (1) application data, and (2) data from web-based surveys.

4.1. Application Data

The application period for the GIA program took place between February and March 2022. During this phase, applicants provided information on priority factors, demographics, income, geographic location, and artistic practice. In total, the application data contains information on 21,921 individuals.

Table 2 — Applicant Priority Factor Characteristics (unweighted)

Variable	N	Proportion	SD
CJ Involved: any past criminal legal system involvement	21921	0.043	0.202
Disability: identify as deaf or disabled	21921	0.104	0.305
LGBTQIA+: identify as LGBTQIA+	21921	0.439	0.496
Transgender: identify as transgender	21921	0.163	0.369
Immigrant: identify as an immigrant to the US	21921	0.191	0.393
BIPOC: identify as Black, Indigenous, or person of color	21921	0.613	0.487
Rural: resident of rural area	21921	0.057	0.231
Caregiver: regularly provide care to another child, adult	21921	0.279	0.449
No safety net: has savings, assets, family resources)	21921	0.920	0.271

Table 3 — Applicant Demographic Characteristics (unweighted)

Variable	N	Proportion	SD
Asian: identify as Asian	21921	0.109	0.311
Black: identify as Black	21921	0.289	0.453
Welfare: receive public benefits (from city, state, or federal)	21921	0.297	0.457
SNAP: receive Supplemental Nutrition Assistance Program	21921	0.141	0.348
Medicaid: receive Medicaid	21921	0.189	0.391
Suburban: resident of suburban area	21921	0.104	0.305
NYC: resident of New York City	21921	0.807	0.395
Bronx: resident of Bronx	21921	0.062	0.241
Brooklyn: resident of Brooklyn	21921	0.366	0.482
Manhattan: resident of Manhattan	21921	0.242	0.428
Queens: resident of Queens	21921	0.126	0.332

Table 4 — Applicant Artistic Characteristics (unweighted)

Variable	N	Proportion	SD
Craft: top-ranked discipline	21921	0.055	0.228
Dance: top-ranked discipline	21921	0.054	0.226
Design: top-ranked discipline	21921	0.055	0.228
Film: top-ranked discipline	21921	0.088	0.283
Literary: top-ranked discipline	21921	0.058	0.234
Media: top-ranked discipline	21921	0.039	0.193
Music: top-ranked discipline	21921	0.230	0.421
Oral Tradition: top-ranked discipline	21921	0.005	0.071
Social Practice: top-ranked discipline	21921	0.012	0.108
Theater: top-ranked discipline	21921	0.094	0.292
Performing Arts: top-ranked discipline	21921	0.023	0.151
Traditional Arts: top-ranked discipline	21921	0.015	0.123
Visual Arts: top-ranked discipline	21921	0.240	0.427
Solo artist: work as a solo artist	21921	0.851	0.356
Collaborative arts: collaborate with arts practitioners	21921	0.688	0.463
Collaborative non-arts: collaborate with non-arts practitioners	21921	0.305	0.460
Involve the public: practice requires public/community involvement	21921	0.436	0.496
Exhibitions: performing/presenting/exhibiting is core to practice	21921	0.624	0.484
Teaching: teaching or educating is core to practice	21921	0.426	0.495

Table 3 represent the priority criteria used for CRNY's weighted lottery in determining which applicants enrolled in the program. Over half of the applicants were non-white, and nearly half were not straight. Over a quarter regularly provided care to others, while almost one in six were transgender. Other disadvantaged or marginalized groups (e.g., immigrants, deaf/disabled) were well represented among the applicants. Table 3 summarizes the demographic, income, and geographic characteristics of the applicants. The mean age of applicants was around 35.7 years. Applicants must have their household income below the Self-Sufficiency Standard (Women's Welfare 2023) for their NY county of residence[1], thus 92% of applicants reported not having a financial safety net. Many report receiving federal public assistance. Geographically, most live in New York City, spread amongst its boroughs. Table 4 summarizes the measures related to their artistic practices. The top-

1. See http://www.selfsufficiencystandard.org/new-york/

listed artistic disciplines ranges widely across the applicants, with music and visual arts the most popular disciplines. The applicants also describe their artistic practice as generally being a solo endeavor although often involving collaborations, exhibitions, and teaching.

4.2. Survey Data

Additional information was collected through a web survey from artists who applied to the GIA program, including both those who had been selected, notified, and enrolled in the program (referred to as the "Enrolled artists" group) and those who were not selected (referred to as the "Control" group). There were two waves of data collection for the enrolled participants and one wave for the control group participants. For both waves, applicants were recruited using an email invitation and two email reminders. Prior to Wave 1, CRNY sent a pre-notification email message alerting artists to expect an email invitation from the Indiana University Center for Survey Research (CSR) and encouraging participation. Survey respondents received a $50 gift card incentive for participation in the Wave 1 survey; for Wave 2, respondents could receive a $75 gift card (if they had also completed the Wave 1 survey) or $50 gift card (if they had partially completed but not finished the Wave 1 survey).

The target population for Wave 1 was artists who applied to the CRNY GIA program in 2022. All 21,169 artists on the sample list provided by CRNY, including both enrolled (n=2,357) and control group (n=18,812) artists, were invited to participate in the Wave 1 survey. At the time of Wave 1, all enrolled artists had already completed the GIA enrollment process and were actively participating in the program. The Wave 1 survey was administered during the final month of each enrolled artist's 18-month participation period, using staggered cohorts of enrolled artists over a five month period, beginning on November 8, 2023 and ending on April 2, 2024, corresponding to the timing of their cohort (Table 1); control group data collection was administered using staggered groups over a two month period beginning on November 8, 2023, and ending on January 5, 2024. A total of 1,315 enrolled artists and 4,384 control group artists completed or partially completed the Wave 1 survey. The American Association for Public Opinion Research (AAPOR) Response Rate 2 for the enrolled group for the Wave 1 survey was 55.8% and the AAPOR Response Rate

2 for the control group for the Wave 1 survey was 23.3%.[2]. The average (median) time to complete the Wave 1 survey was 21 minutes (enrolled artists) and 17 minutes (control group artists).

The target population for Wave 2 was enrolled artists who answered at least one question in the core survey for Wave 1. All 1,315 artists who met this criterion were invited to participate in the Wave 2 survey. Control group artists were not included in Wave 2 data collection. The Wave 2 survey was administered three months after the conclusion of the GIA program for each participant, again using staggered cohorts of enrolled artists over a five-month period, beginning on February 8, 2024, and ending on July 2, 2024. A total of 944 enrolled participants completed or partially completed the Wave 2 Survey; the AAPOR Response Rate 2 for Wave 2 was 71.8%. The median time to complete the Wave 2 survey was 18 minutes.

The survey questionnaire consisted of a mix of matrix (Likert), closed-ended, and some open-ended questions focused on artistic practice(s), the amount of time spent on these practices, funds earned from these practices, financial health, living situations, and the artist's overall health and well-being, as well as a set of demographic items. Many of these questions were adapted from the CRNY Guaranteed Income application. The questionnaire was nearly the same for enrolled artists and control group artists.

The instrument was developed over several months through an iterative, collaborative process that involved staff from the Center for Survey Research at Indiana University, as well as members of the research team working on this evaluation. The development team included scholars in economics, social work, public affairs, and culture, who collectively ensured that the instrument would yield valid, relevant, and multidimensional measures of artists' labor, income, and well-being. Where available, we collected and reviewed survey instruments from prior evaluations of guaranteed income programs to use as templates or reference points.

In addition, we consulted with David Throsby and Katya Petetskaya, drawing on their extensive experience surveying artists in Australia, to inform the structure and phrasing of

2. While Vivalt et al. 2024 had response rates over 95%, more typical response rates for evaluations are in the range of 50% to 60% (e.g., Balakrishnan et al. 2024, West and Castro 2023)

items specifically focused on artistic labor and earnings (Throsby and Petetskaya 2024). We also engaged with an artist advisory group, composed of practicing artists, who reviewed the draft questionnaire and provided feedback that shaped several revisions to improve clarity, cultural relevance, and resonance with artist experiences. Finally, the instrument underwent thorough testing, including internal cognitive review, pilot testing, and technical checks, to ensure its reliability and usability across a broad and diverse respondent population.[3]

4.3. *Labor Market Outcome Measures*

To measure the labor supply impacts of guaranteed income, this analysis uses several indicators from the survey. We measure time spent on work in two ways: first using a binary variable indicating whether the respondent participated in the labor-force; and second, using a continuous measure of labor intensity, defined as the number of hours worked per week over the past month. In addition, self-reported earnings from labor are measured using survey questions that ask for current gross earnings over weekly, monthly, or yearly time-frames (respondents' choice). Respondents were asked for each of these labor supply variables (participation, hours, earnings) separately for three different types of work: (a) artistic or cultural practice work, (b) arts-related work, and (c) non-arts work. This categorization of work takes advantage of prior research on the artistic workforce that recognizes how artists often work – concurrently or separately – in ways that engage creative practice (e.g., writing music), that use artistic talents but may not be creative themselves (e.g., teaching music), or that do not involve arts (e.g., retail sales). Survey questions recognized that respondents may be working as employees, as freelancers or independent contractors, or a combination. Reported participation, hours, and earnings are inclusive of all sources of wages.

Table 5 shows descriptive statistics for these outcome measures. Earnings are reported here in annualized terms to improve comparability. Most respondents indicated that they worked some time on all three types of work over the past 12 months. Only 5% indicated no arts work in the past year. The sample of respondents reported working an average of

3. The survey questionnaire is available upon request to the authors.

about 45 hours per week over the past month, with arts work accounting for almost half of that. Earnings fluctuated widely across the sample, especially for work in artistic or cultural jobs.[4]

Table 5 — Descriptive Statistics for Labor Supply Measures

Variable	N	Mean	SD
Participation – arts work (0/1)	5353	0.948	0.221
Participation – arts-related work (0/1)	5350	0.722	0.448
Participation – non-arts work (0/1)	5343	0.708	0.455
Hours – arts work (weekly)	5699	20.283	19.030
Hours – arts-related work (weekly)	5699	9.955	13.674
Hours – non-arts work (weekly)	5699	14.865	17.931
Earnings – arts work (annual, USD)	5699	20825.79	586390.80
Earnings – arts-related work (annual, USD)	5699	8210.42	30375.67
Earnings – non-arts work (annual, USD)	5699	13172.25	54652.50
Earnings – total (annual, USD)	5699	42208.47	616000.00

Note: Participation is a binary variable indicating whether the respondent reported any hours in a given category. Hours reflect average weekly hours worked in the past month. Earnings are self-reported annual income in U.S. dollars.

5 — Methods

Measuring the impacts of guaranteed income on individuals' labor supply requires identifying an appropriate counterfactual for the program participants. The GIA program had the advantage of randomly assigning a subset of eligible applicants for participation in the program. Randomization of applicants into the treatment allowed us to distinguish the treatment effect from a selection effect. In addition, because the control group of non-selected applicants' labor supply was also observable (using an identical survey instrument) concurrently with the participants, a suitable comparison group was available to establish

4. Earnings responses exhibited large variances, especially for the earnings in arts work. Some high values might reflect inconsistent responses to the frequency of pay. To test for sensitivity of our results to these high values, we conservatively recoded the reported frequencies to limit earnings to the 99th percentile of earnings for those reporting annual earnings (as opposed to weekly or monthly). This cap at, for example, $80,000 per year for arts earnings reduces the standard deviation of arts earnings to 23,481. The main findings (sign, significance) do not, however, change.

the counterfactual. Therefore, we identified the effects of the program on labor supply by comparing the treatment and control groups.

The analysis also introduced propensity weights to account for the GIA's weighted lottery and separate the treatment effect from confounding factors. Because the factors that determined the weights in the GIA lottery (called "priority criteria") were known, the analysis involved using propensity scores that directly accounted for the probability of assignment to treatment. Furthermore, because the outcome measures were observed only for survey respondents, sample weights were used to address possible response bias in the survey data. These sample weights and treatment weights, taken together, achieved a strong balance on baseline characteristics between the treatment and control groups and give us confidence that differences in outcome measures are owed to the GIA treatment.

Tables 6 and 7 show the unweighted and weighted sample means for these same covariates for the study sample. Raw sample means for the treatment and control groups may differ due to the weighted lottery and differential nonresponse rates for GIA participants. The significant differences in unweighted means in Tables 6 and 7 reflect this imbalance in sample characteristics for many covariates. The priority criteria determining the weighted lottery (shaded rows in Table 6) highlight this imbalance. The imbalance in pretreatment characteristics extends to some race and geographic indicators as well as some of the artistic disciplines (e.g., Craft, Design, Music, Visual Arts). Yet the unweighted means for some aspects of artistic practice, age, and public assistance receipt reveal no significant differences. The weighted means illustrate that most of these differences are addressed with the treatment and sample weights estimated here. As expected, the priority criteria variables go from being very unbalanced to closely balanced after the weights. Some of the initially unbalanced geographic indicators improved their balancing after weighting. Insofar as the probability of selection in the GIA weighted lottery correlates with geographic, artistic practice, or other baseline characteristics, some imbalance may remain after weighting.

Table 6 — Study Sample Demographic Characteristics

Variable	Unweighted			Weighted		
	Mean (participant)	Mean (control)	t-stat	Mean (participant)	Mean (control)	t-stat
CJ Involved	0.046	0.038	1.225	0.036	0.040	-0.613
Disability	0.154	0.116	3.614	0.106	0.105	0.069
LGBTQIA+	0.510	0.483	1.679	0.469	0.449	1.071
Transgender	0.216	0.175	3.326	0.172	0.167	0.369
Immigrant	0.197	0.190	0.524	0.185	0.190	-0.308
BIPOC	0.600	0.533	4.298	0.601	0.607	-0.320
Rural	0.126	0.053	9.136	0.056	0.054	0.341
Caregiver	0.331	0.241	6.548	0.255	0.266	-0.688
No Safety Net	0.935	0.906	3.267	0.929	0.922	0.745
Age	36.468	36.079	1.014	34.915	35.343	-1.074
Asian	0.139	0.126	1.280	0.110	0.108	0.186
Black	0.260	0.208	4.038	0.285	0.284	0.016
Welfare	0.325	0.334	-0.572	0.289	0.295	-0.375
SNAP	0.150	0.157	-0.645	0.131	0.140	-0.679
Medicaid	0.223	0.228	-0.384	0.191	0.190	0.066
Suburban	0.151	0.095	5.774	0.102	0.103	-0.121
NYC	0.653	0.825	-13.475	0.809	0.812	-0.284
Bronx	0.064	0.044	3.016	0.047	0.056	-1.302
Brooklyn	0.254	0.388	-8.956	0.389	0.377	0.636
Manhattan	0.169	0.255	-6.472	0.228	0.245	-1.047
Queens	0.158	0.130	2.587	0.134	0.125	0.814

Table 7 — Study Sample Artistic Characteristics

Variable	Unweighted			Weighted		
	Mean (participant)	Mean (control)	t-stat	Mean (participant)	Mean (control)	t-stat
Craft	0.062	0.042	3.006	0.044	0.051	-1.039
Dance	0.061	0.055	0.874	0.053	0.054	-0.042
Design	0.053	0.039	2.209	0.046	0.052	-0.928
Film	0.100	0.083	1.819	0.090	0.088	0.213
Literary	0.082	0.075	0.847	0.064	0.059	0.658
Media	0.049	0.029	3.435	0.035	0.035	-0.047
Music	0.157	0.205	-3.853	0.223	0.228	-0.301
Oral Tradition	0.005	0.003	1.427	0.003	0.004	-0.746
Social Practice	0.011	0.010	0.193	0.006	0.011	-1.830
Theater	0.116	0.113	0.292	0.114	0.099	1.425
Performing Arts	0.026	0.022	0.843	0.023	0.023	-0.181
Traditional Arts	0.016	0.012	1.019	0.009	0.014	-1.377
Visual Arts	0.220	0.276	-4.036	0.249	0.248	0.063
Solo artist	0.856	0.862	-0.595	0.852	0.855	-0.225
Collaborative arts	0.690	0.694	-0.218	0.707	0.694	0.782
Collaborative non-arts	0.318	0.310	0.572	0.298	0.307	-0.550
Involve the public	0.443	0.443	-0.054	0.431	0.435	-0.219
Exhibitions	0.618	0.646	-1.807	0.645	0.626	1.011
Teaching	0.443	0.436	0.443	0.433	0.428	0.305

The primary analysis aimed to assess the impact of cash transfers on work outcomes using the following regression model:

$$Y_i = \alpha + \beta \text{Treated}_i + \epsilon_i \tag{3}$$

where *Y* represents the post-treatment outcome variable, and *Treated* is an indicator variable for whether the individual received the treatment. The term α is the intercept, β represents the estimated treatment effect, and ϵ is the error term. Estimates of β tell us the average treatment effect (ATE) of participation in the guaranteed income program on individual labor supply. Using weights to account for different propensities for treatment and survey nonresponse, the simple model leverages the randomized nature of the GIA program to identify the ATE.

The model directly examines key elements of Throsby's work-preference model (Throsby 1994). Throsby's model posits that artists derive intrinsic utility from their work, which contrasts with the standard economic assumption that individuals experience disutility from labor. Non-arts wages higher than arts wages can support some mix of arts and non-arts work, especially if a subsistence constraint binds. The GIA applicant population, with income under the SSS, provides a strong fit for Throsby's setting. Less than 37% of applicants performed no non-arts work ($L_n = 1$) and only 8% performed only arts work. The increase in unearned income from the GIA may affect labor supply by altering the likelihood or intensity of working for pay. The marginal propensity to earn (MPE) literature suggests that an increase in unearned income is generally associated with a reduction in earnings (Golosov et al. 2024; Auclert, Bardóczy, and Rognlie 2023), though the magnitude of the reduction is uncertain. Thus, the more general labor literature on MPE might predict $\beta \leq 0$ for hours worked irrespective of the type of labor (arts, arts-related, non-arts). By contrast, the work-preference model predicts β < 0 for non-arts work hours and β > 0 for arts work hours. According to the work-preference model, higher wages in non-artistic sectors generally motivates artists to allocate more time to non-artistic work, especially if the subsistence consumption constraint demands a minimum income for survival. Yet a guaranteed income (i.e., relaxing the subsistence constraint) allows reallocation of labor from non-arts to arts. The regression equation, therefore, provides a direct test of how a basic income affects artists' labor supply decisions, validating Throsby's hypothesis that pecuniary wages are less important to artists than to other workers, and that their labor supply is more heavily influenced by non-monetary factors related to their artistic preferences.

5.1. Robustness Checks

Estimating equation (1) for a particular outcome measure yields an ATE estimate, but important limitations remain. For instance, the ATE estimate says nothing about possible effect heterogeneity. Guaranteed income might affect various subpopulations differently, with some more or less responsive to the cash transfer. Although the primary interest here is in identifying average effects on labor supply from this program, an initial exploration into heterogeneous effects is possible. To that end, equation (1) can be expanded to include a dummy variable for a particular subgroup and its interaction with the *Treated* variable.

$$Y_i = \alpha + \beta \text{Treated}_i + \gamma \text{Type}_i + \delta \text{Treated*Type}_i + \epsilon_i \tag{4}$$

Estimating the coefficient on the interaction term (δ) via weighted least squares provides insight into possible heterogeneous effects. For this exploratory analysis, several alternative subgroups were tested for each of the outcome measures. The analysis tested for significant interaction terms for certain (pretreatment) demographic indicators (e.g., Man, Woman, BIPOC, age $\geq$ 45, age < 30), dummies for caregiving status, college degree, part-time work status, and NYC residence, and an indicator for whether primary artistic discipline was more commercially oriented (i.e., design, film, media, music). Significant interaction terms in the basic model suggest stronger or weaker impacts on that particular subgroup.

Despite the randomized nature of selection into the GIA program and the propensity weights applied, concern might arise that other confounders could affect labor supply. To address this, equation (1) was also estimated with baseline covariates included as control variables. These robustness checks, conducted for each of the outcome measures, used a vector of controls composed of the priority criteria, dummies for man and woman, age, years of education,[5] and an indicator for more commercial disciplines. Estimating separate models for each of the outcome measures does not allow for cross-equation correlations among the errors. To address this, the models with control variables can be estimated in a simultaneous equation model. Furthermore, concern arises that in testing so many hypotheses that the analysis may be prone to incorrect rejections of the null ($\beta = 0$). To address this false discovery rate (FDR) concern, the analysis also reports sharpened two-stage q-values (Benjamini and Yekutieli 2006) as described in Anderson (2008). The resulting q-values offer more robust information about the significance of the hypotheses tests.

Lastly, similar to the Bartik et al. (2024) approach, a LASSO technique is adopted to ex-

5. This variable was not measured the application data, therefore is not included in the vector of covariates for constructing the weights. In this context, years of education should not be endogenous to labor supply given that artists in the sample have already completed their education and are making short-term labor supply decisions based on current market conditions rather than educational investment.

plore an even larger set of pretreatment covariates in a simultaneous equations estimation setting. The LASSO applies a penalty term λ based on a plugin method dependent on the data. The LASSO procedure starts with all covariates used in establishing the weights (see Tables 3 and 4) and their interactions with *Age*. This exercise, performed separately for each outcome measure, always includes the treatment variable and otherwise yields a different selected subset of covariates for each outcome. The outcome-specific model specifications selected by the LASSO are then included in a system of simultaneous equations estimated to identify the treatment effects. Again, FDR corrections are applied to adjust the p-values for these results.

6 — Results

6.1. Time Spent on Work

The results across Tables 8, 9, and 10 evaluate the impact of guaranteed income on time allocation and engagement in different types of work, including arts, arts-related, and non-arts work. The results are grouped into three primary work categories: arts work, arts-related work, and non-arts work, analyzed across three dimensions—work participation (yes/no), hours spent, and earnings. The concept of artists contributing to various labor markets, both arts and non-arts, comes from the work-preference model (Throsby 1994) that allows labor supply to be a function of not only income, but also personal satisfaction from the type of work individuals enjoy. Artists have long been associated with intrinsic motivational factors for pursuing arts work and thus the work-preference model is especially apt to their circumstances.

Guaranteed income increased the likelihood of engaging in arts work, with a statistically significant treatment effect of 0.032 ($t = 4.364$, $p < 0.001$), compared to the control mean of 0.938. It also increased engagement in arts-related work, with a treatment effect of 0.050 ($t = 3.021$, $p < 0.001$). Conversely, participation in non-arts work decreased by 0.050 ($t = -2.741$, $p < 0.001$). These results suggest that guaranteed income supports greater participation in arts-related activities while reducing reliance on non-arts work.

Table 8 — Impact of Guaranteed Income on Time Spent on Work (Binary Outcomes, OLS Regression)

Yes/No	N	Control Mean	Treatment Effect	t-stat
Arts Work	5353	0.938	0.032	4.364***
Arts-Related Work	5350	0.703	0.050	3.021***
Non-Arts Work	5343	0.717	-0.050	-2.741***

Note: *, **, *** indicate p-values < 0.1, 0.05, 0.01, respectively.

Participants in the treatment group spent significantly more hours on arts work, with an increase of 3.884 hours per week ($t = 5.580$, $p < 0.001$) over the control mean of 19.36 hours. Hours spent on arts-related work showed no significant change ($t = 1.109$). However, hours spent on non-arts work decreased significantly by 2.382 hours per week ($t = -3.865$, $p < 0.001$), compared to the control mean of 15.30 hours. These results suggest that the increase in arts work slightly outweighed the reduction in non-arts work.

Table 9 — Impact of Guaranteed Income on Hours Spent on Work (Continuous Outcomes, OLS Regression)

Hours	N	Control Mean	Treatment Effect	t-stat
Arts Work	5699	19.354	3.884	5.580***
Arts-Related Work	5699	9.740	0.560	1.109
Non-Arts Work	5699	15.297	-2.382	-3.865***

Note: *, **, *** indicate p-values < 0.1, 0.05, 0.01, respectively.

Overall, guaranteed income enabled participants to reallocate their time and focus toward arts-related activities. It increased the likelihood of engaging in arts work and decreased both participation and time allocated to non-arts work. These results suggest that financial support reduces economic pressures, allowing participants to prioritize creative and arts-related pursuits without significantly diminishing overall work engagement.

6.2. Earnings

The results in Table 10 assess the impact of guaranteed income on participants' annual earnings from different work categories.

Guaranteed income did not significantly affect earnings from arts work, with a negative treatment effect of $7,290.60 ($t = -0.726$), relative to a control mean of $22,825.36.

Additionally, earnings from arts-related work did not change significantly. Earnings from non-arts work decreased significantly by $3,680.06 (t = -2.726, p < 0.001), relative to a control mean of $13,759.69. This reductions suggests that participants receiving guaranteed income may rely less non-arts work for income.

The results show that guaranteed income appears to reduce participants' earnings in non-arts work. The lack of significant impact on arts work earnings may indicate that guaranteed income enables participants to prioritize their artistic endeavors without needing to maximize earnings in this area. Meanwhile, the reduction in non-arts earnings suggest a possible shift in financial reliance, where guaranteed income supplements or replaces income from less desirable or less consistent sources. This aligns with the broader goal of financial stability and reduced economic pressure, allowing participants to focus more on intrinsic or creative pursuits.

Table 10 — Impact of Guaranteed Income on Annual Earnings (Continuous Outcomes, OLS Regression)

Earnings/Year	N	Control Mean	Treatment Effect	t-stat
Arts Work	5699	22825.359	-7290.604	-0.726
Arts-Related Work	5699	8248.059	-620.709	-0.704
Non-Arts Work	5699	13759.687	-3680.059	-2.726***
Total Earnings	5699	44833.104	-11591.372	-1.094

Note: *, **, *** indicate p-values < 0.1, 0.05, 0.01, respectively.

Overall the results highlight that the program shifted participants' focus towards arts-related work, as evidenced by increases in participation and hours worked in arts activities and corresponding decreases in non-arts work. However, their earnings from arts work and arts-related work showed no changed or slightly declined, suggesting that these participants may have prioritized less commercially viable but more personally meaningful projects. The estimated effect on total annualized earnings has a wide confidence interval, but its point estimate (-$11,591.37) is rather close to the $12,000 per year that the GIA provided participants. Overall, and consistent with the work-preference model, artists receiving the cash transfer generally reduced earnings to keep net income unchanged while shifting their work allocation from non-arts work to arts work, even working more hours although not enjoying more pecuniary gains. The results in this section represent the most straightforward set of results, although additional robustness checks are possible in case of confounders, cross-equation correlations in errors, or potential false discoveries.[6]

Results in the Appendix show how very stable these basic results are to estimating with a basic or an extended set of controls, to allowing for cross-equation correlations, and to FDR adjustments. Point estimates of effect sizes are generally quite stable. Comparing the basic model results with models using a vector of controls (Table 11), in a set of Simultaneous Equation Models (Table 12), and LASSO-specified models (Table 13) suggests that the additional controls and robust estimation change little.[7] The decrease in non-arts hours offsets the increase in arts hours more, and the negative earnings impacts grow somewhat. Otherwise, the results exhibit considerable stability in the face of these other estimation approaches.

7 — Discussion

The findings of this study contribute to understanding both the empirical validity of Throsby's work-preference model and the role of non-labor income in shaping labor supply for artists. By examining the effects of CRNY's GIA program, the study demonstrates how guaranteed income enables artists to reallocate their time, increasing hours spent on creative work while reducing engagement in non-arts employment. This shift aligns with Throsby's model, which posits that artists derive intrinsic utility from their craft and prioritize artistic labor over monetary compensation when financial stability is provided. The increase in hours dedicated to arts-related work underscores the potential of non-labor income, such as guaranteed income, to mitigate the economic pressures that often push artists into non-creative jobs, thereby enabling them to focus on their artistic practices.

At the same time, the study reveals a substitution effect, where guaranteed income replaces earnings from non-arts work, leading to a decline in hours spent in non-creative employment. This further supports the notion that non-labor income has a positive effect

6. We also conducted a heterogeneity analysis analyzing the impacts of guaranteed income across various non-priority factor variables., including sex, age, commercial art discipline (e.g., design, film, media, music), part-time employment status, college degree attainment, and location (New York City). This analysis offers an initial exploration into whether the effects of the cash transfer vary meaningfully across demographic or occupational categories. Overall, the evidence suggests limited heterogeneity in treatment effects across most groups or outcomes.

7. Tables 11, 12, and 13 are located in the Appendix.

on labor supply by reducing the need for artists to seek income from other sectors. However, the decline in non-arts earnings raises important questions about the sustainability of such programs, suggesting that while non-labor income can facilitate greater artistic engagement, it may need to be paired with other support mechanisms to ensure long-term economic stability for artists.

These findings not only reinforce Throsby's work-preference model by showing how financial stability allows artists to prioritize their craft, but also echo Hans Abbing's (2008) argument that many artists are motivated more by intrinsic than extrinsic rewards. As Abbing points out, and Throsby (2004) agrees with, the work-preference leads artists to accept low earnings and uncertain prospects in exchange for the non-monetary satisfaction of creative work. From this perspective, the persistent poverty of artists may not only result from market failure but also from a rational response to deep-seated preferences. In this light, guaranteed income programs help reconcile the tension between artists' intrinsic motivations and the demands of a market-oriented economy, though Abbing's skepticism about traditional subsidies reminds us that such interventions must be carefully designed to avoid reinforcing unrealistic expectations or oversupply in the sector (Towse 2019).

These findings also contribute to a broader understanding of the distinctive structure of artistic labor markets, which have long been characterized by volatility, fragmentation, and weak institutional supports. Menger's (1999) seminal analysis describes these markets as marked by chronic oversupply, discontinuous employment, and career unpredictability, features that help explain why artists are often forced to engage in multiple job-holding and adopt hybrid work arrangements. Throsby and Zednik (2011) further demonstrate that many artists pursue parallel careers—often out of necessity—balancing creative pursuits with non-arts employment to secure a minimum income threshold. While such arrangements can support artistic continuity, they also reflect the ongoing tension between creative autonomy and economic survival.

Recent scholarship deepens this portrait of labor market complexity. For instance, Alacovska and Bille (2021) emphasize the diverse and hybrid economies in which artists operate, spanning market, gift, and informal exchanges. Similarly, Feder and Woronkowicz (2023) and Bosma et al. (2024) identify a divide between artists who pursue self-employment willingly and those who enter it reluctantly, highlighting the often-constrained agency artists face in shaping their careers. These studies underscore that artists' labor supply decisions cannot be fully understood without accounting for the institutional and structural conditions that limit their choices.

At the same time, these findings resonate with the sociological literature that has long cautioned against romanticizing artistic independence. Lingo and Tepper (2013) argue that arts-based careers are deeply shaped by institutional gatekeeping, social networks, and structural inequalities—factors that guaranteed income alone cannot address. Likewise, Baldin and Bille (2022) show how artist identities and career outcomes vary widely depending on education, recognition, and orientation toward the market. As Skaggs and Aparicio (2023) note, definitional ambiguity around who counts as an "arts worker" complicates efforts to build collective responses to precarity. Thus, while guaranteed income demonstrates measurable benefits for artistic labor supply, it should be viewed as one component in a broader ecosystem of support. As Woronkowicz (2025) argues, lasting improvements in artistic careers will require more systemic change—rethinking not only how artists are supported, but how their labor is recognized, valued, and integrated into the wider economy.

This study also raises broader questions about the role of guaranteed income in addressing systemic inequities in the arts sector. Existing research has shown that inequality in the arts is deeply rooted in gender, race, class, and geography, and is perpetuated by institutional structures and labor market dynamics. For example, women and BIPOC artists continue to face significant pay gaps and underrepresentation in leadership roles, as demonstrated by (Dowd and Park 2024) in their analysis of gendered pay disparities among composers and by (Lindemann, Rush, and Tepper 2016) in their study of asymmetrical income outcomes across genders. Guaranteed income programs like CRNY's may serve as partial correctives by providing artists outside traditional power centers or from marginalized groups with the financial flexibility to sustain their practice and build careers in a structurally unequal field. Woronkowicz and Noonan (2024) argue that institutional innovations are essential to challenging the status quo, and unconditional cash transfers represent one such intervention that bypasses traditional gatekeeping mechanisms. Nevertheless, as noted by

Woronkowicz (2024), deeper structural inequities related to access, education, and representation may require more comprehensive and sustained policy efforts.

Throsby's work-preference model for artists appears to hold true. Artists receiving basic income would not work less, but would instead shift their labor from non-creative work to their (more personally rewarding) artistic pursuits. In that sense, a double-dividend from the payments arise for artist recipients: they gain the guaranteed income cash transfer as well as increased "psychic income" from additional work in their preferred, creative activity. Moreover, the work-preference model underscores how a strictly pecuniary analysis misses the important, positive welfare effects arising from non-pecuniary benefits to artists. A cash transfer might not work well to get artists' incomes well above the subsistence level, but its benefits are still substantial for artists.

8 — Conclusion

Like any study, there are various limitations to how we examine the effect of guaranteed income on artists' labor supply. One important limitation of this study concerns the definition of "artist." The CRNY program adopted a notably inclusive eligibility criterion—defined as "an inclusive interpretation that captured diverse artistic practices." Specifically, CRNY defined artists as individuals who "regularly engage in artistic or cultural practice to express themselves with the intention of communicating richly to or sharing with others; pass on traditional knowledge and cultural practices; offer cultural resources to their communities; and/or co-organize and co-create within communities toward social impacts" (Creatives Rebuild New York 2022, p. 5). This broad definition encompassed not only conventionally recognized artists—such as painters, musicians, dancers, and writers—but also practitioners of community arts, traditional cultural bearers, and socially engaged creatives who may operate at the margins of the commercial arts economy.

This expansive framing challenges conventional classifications, such as those based on the U.S. Census Bureau's Standard Occupational Classification (SOC) system, which tends to undercount artists who do not report art as their primary occupation or whose artistic output is not commercially oriented. As explored in Woronkowicz, Noonan, and Malone

(2025), applying narrow occupational definitions risks excluding substantial segments of the artistic workforce—particularly individuals from marginalized backgrounds or those practicing in under-commercialized disciplines. At the same time, this inclusivity complicates generalization beyond a specific segment of artists—namely, those facing relatively high economic vulnerability and unstable attachment to market-based arts income. We therefore caution against extrapolating these findings to higher-earning or more commercially integrated artists, for whom income stability may generate different labor supply responses.

A further limitation is the potential for social desirability bias, particularly among the treatment group, who may feel inclined to overstate their engagement in artistic work in an effort to reflect well on the program or its funders. Such bias could lead to an overestimation of treatment effects. That said, because all weighting variables and pre-treatment measures were collected prior to program participation, baseline comparisons are not affected by post-treatment reporting incentives, mitigating concerns about differential selection bias.

The theory we test—Throsby's work-preference model—is nevertheless applicable across artistic types, since it hinges not on occupational classification per se, but on the intrinsic motivation to create and the trade-offs artists make between artistic and non-artistic labor. Testing this model among economically vulnerable artists may be especially informative, as these individuals are likely closer to the subsistence constraints that Throsby identified as key to understanding labor supply behavior. However, this also implies that the observed effects reflect responses under conditions of financial strain, rather than unconstrained artistic choice.

Another important limitation of this study is its temporal context. The guaranteed income program was implemented in the immediate aftermath of the COVID-19 pandemic, a period of exceptional disruption in the arts labor market. Artists' responses to the income support may therefore reflect recovery dynamics—such as rebuilding routines, stabilizing housing, or re-establishing creative practice—rather than longer-term adjustments in labor allocation. This context likely amplified the value of income stability while also constraining the range of feasible behavioral responses. As a result, the estimated effects should not be interpreted as representative of guaranteed income impacts under more stable economic conditions.

The study also abstracts from substantial heterogeneity in artists' circumstances. Although we observe an average increase in artistic labor and a reduction in non-arts work, these aggregate shifts likely mask divergent uses of time and income. For artists facing chronic health issues, caregiving responsibilities, discrimination, or immigration precarity, the guaranteed income may have primarily supported basic stability rather than expanded creative production. In this sense, increased artistic hours should not be interpreted solely as productivity gains but, in some cases, as the restoration of capacity to remain active at all. Preliminary evidence suggests that improvements in physical and mental health were a central benefit for many participants (S. Cowan et al. 2025), underscoring the importance of distinguishing between creative output, labor input, and well-being in future research.

Because the intervention is a cash transfer, any policy discussion must confront both the budgetary outlay and what else those resources could have funded. For the artists who applied to CRNY—an applicant pool often characterized as economically precarious—receiving $1,000 per month corresponds to approximately 16 more hours of artistic work and roughly 10 fewer hours of non-arts work, or a net change of about 6 working hours per month. These estimates document behavioral responses consistent with the work-preference model; they are not a benefit metric, nor an endorsement of guaranteed income. Assessing cost-effectiveness would require valuing outcomes beyond hours and comparing alternative instruments.

At the same time, the adequacy of the $1,000 stipend must be evaluated relative to recipients' baseline economic insecurity. According to the Self-Sufficiency Standard for New York State, the income required to meet basic needs varies widely—from under $30,000 annually for a single adult in some rural areas to over $100,000 for a single parent with two children in parts of New York City (Pearce and Brooks 2000). For many participants, the stipend functioned less as an income replacement than as a stabilizing supplement, reducing volatility rather than ensuring sufficiency. Understanding how different payment levels alter labor supply, well-being, and longer-term career outcomes remains an important direction for future research.

Survey data from the program underscore how significant this financial support was for participants. As documented in the financial well-being report, "against this backdrop of pervasive financial uncertainty, the GI payments emerged as a source of relief for many participants. In survey responses, artists who received GI almost uniformly agreed that the payments helped them afford basic expenses and supported their artistic and cultural practice. They also rated their own financial stability higher than peer artists" (Sarah Cowan et al. 2025).

The temporary nature of the CRNY program further shapes interpretation. Because the initiative was explicitly time-limited, artists may have treated it as a short-term buffer rather than a permanent income floor. This may have dampened some responses while amplifying others, such as short-term re-engagement with artistic practice or investment in recovery rather than long-term career restructuring. Longitudinal data are therefore essential to assess whether these shifts persist after payments end or translate into durable changes in earnings, output, or professional stability.

Within these constraints, guaranteed income nevertheless serves as a rare and powerful policy instrument for empirically testing a longstanding theory of artistic labor behavior—Throsby's work-preference model. By offering unconditional support, programs like CRNY's GIA allow researchers to observe how artists reallocate labor when immediate subsistence pressures are relaxed. In doing so, these programs provide one of the most direct and rigorous tests of Throsby's central hypothesis: that artists, when financially secure, will prioritize their creative practice over the pursuit of higher earnings. The evidence from this study affirms this prediction. Rather than withdrawing from the labor force or increasing leisure time, participating artists intensified their engagement in artistic work and reduced their reliance on non-arts employment—precisely the behavior Throsby theorized decades ago.

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9 — Appendix A: Weighting Procedures

Generalized Boosted Models (GBM) can be used to create both sample and treatment weights in survey and observational studies, addressing biases from nonresponse and treatment assignment. This analysis applied GBM in two stages. First, GBM estimated the probability of responding to the survey using a wide array of pretreatment variables, generating sample weights as the inverse of these probabilities. Second, GBM estimated the probability of receiving treatment while incorporating the sample weights, producing treatment weights based on the exact set of pretreatment covariates used in the weighted lottery. Ultimately, the final weights combined sample and treatment weights, ensuring that the analyses accounted for both processes, enabling unbiased estimation of population parameters and causal effects. We provide details on how we created the weights in the Appendix.

Nonresponse in surveys poses a significant risk of bias, particularly when the likelihood of responding is systematically associated with key study variables. To address this challenge, nonresponse weights are often constructed to adjust for differences between respondents and nonrespondents. GBM offers a robust and flexible approach to creating these weights by leveraging their ability to model complex, nonlinear relationships in data.

GBM is a machine learning technique that builds an ensemble of weak learners, typically decision trees, to predict an outcome (Friedman 2001). Unlike traditional parametric approaches, GBM is nonparametric, allowing it to adapt to intricate patterns and interactions in the data. This flexibility is especially valuable when modeling survey response probabilities, which are often influenced by a diverse set of factors, such as demographic characteristics, survey design features, and behavioral variables.

The process began by defining a binary response indicator R_i for each unit i in the sample:

$$R_i = \begin{cases} 1 & \text{if unit } i \text{ responds,} \\ 0 & \text{if unit } i \text{ does not respond.} \end{cases}$$

Covariates X, available for both respondents and nonrespondents, were then identified as predictors. These variables were both predictive of the likelihood of response and available for the entire sample. Covariates used in this analysis included: dummies for whether the applicant had any of the priority criteria and variables measuring age, race, receipt of public assistance, residential location, artistic discipline, and artistic practices. (The full set of covariates X used in estimating nonresponse weights can be found in Table 3 and Table 4.)

A GBM model was then fitted to estimate the probability of response, $P(R_i = 1 \mid X_i)$, for each unit i. GBM works iteratively, building a series of decision trees, with each successive tree aiming to correct the errors of the previous ones (Hastie et al. 2009). At each step, the model minimizes a loss function, such as deviance, to improve predictive accuracy. The probability of response, denoted as $\hat{P}_i$, is calculated for each unit after training the GBM.

The next step involved deriving sample weights based on these predicted probabilities. The weight for a given respondent was computed as the inverse of their predicted probability of response:

$$w_i = \frac{1}{\hat{P}_i}.$$

This approach assigned higher weights to units with lower probabilities of response, compensating for their underrepresentation in the sample. Tables 3 and 4 illustrate the unweighted means for covariates used to create the sample weights. They also show the baseline characteristics of the applicant population.

In many applications, particularly in observational studies, researchers are interested in estimating causal effects of a treatment. To do so, propensity score weighting is often employed, where the weights are based on the predicted probability of receiving the treatment. When nonresponse is also a concern, it is essential to combine the treatment and sample weights to account for both processes.

The treatment indicator, T_i, is defined for each unit as:

$$T_i = \begin{cases} 1 & \text{if unit } i \text{ receives the treatment,} \\ 0 & \text{if unit } i \text{ does not receive the treatment.} \end{cases}$$

To create treatment weights, a GBM model was used to estimate the probability of receiving the treatment, $P(T_i = 1 \mid X_i)$, for each unit i. This model incorporated the set of covariates used by CRNY in constructing their weighted lottery (i.e., the priority criteria) as well as the geographic and other baseline characteristics in Tables 3 and 4. Additionally, the sample weights w_i were included in the model to adjust for the nonresponse process during the estimation of treatment probabilities. This ensures that the treatment model is estimated based on a sample that reflects the population of interest. Thus, the combined weights adjust for the dual processes of nonresponse and treatment assignment, allowing for unbiased estimation of causal effects in the presence of nonresponse (McCaffrey, Ridgeway, and Morral 2004).

Tables 6 and 7 illustrate the covariates used in the weighting process adjusted for the dual weights, by treatment and control group. Diagnostic plots confirm the effectiveness of the weights in achieving balance in the baseline covariates. Figure 3 plots the standardized differences (between treatment and control groups) for all covariates, where hollow circles indicate insignificant differences, to highlight how the weights improved balancing. Weighted absolute standard differences of covariates tend to be small. Figure 4 shows how the unweighted pretreatment variables differ significantly between treatment and control (i.e., low p-values) for many covariates, as expected, given the weighted lottery. After weighting, the p-values are much higher; generally higher than the 45-degree line associated with a cumulative distribution of a uniform variable, which suggests the balancing was even better than what would be expected from a fully randomized study. As both stopping rules (based on the mean of effect sizes, es.mean, or on the maximum of individual Kolmogorov-Smirnov statistics, ks.max) yield similar diagnostics, we use ks.max.

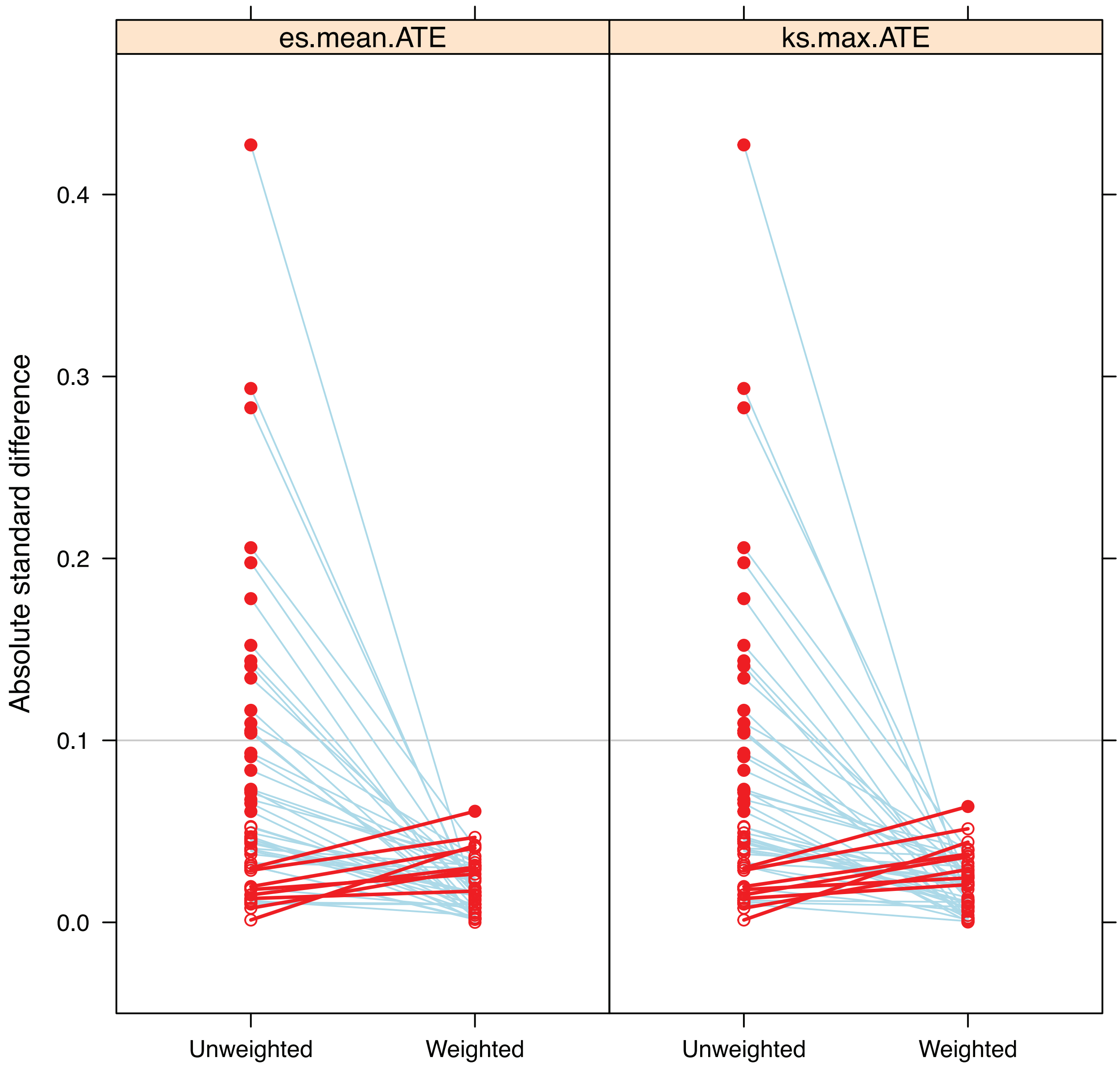

Figure 3 — Effectiveness of GBM weighting in balancing covariates, for two alternative stopping rules.

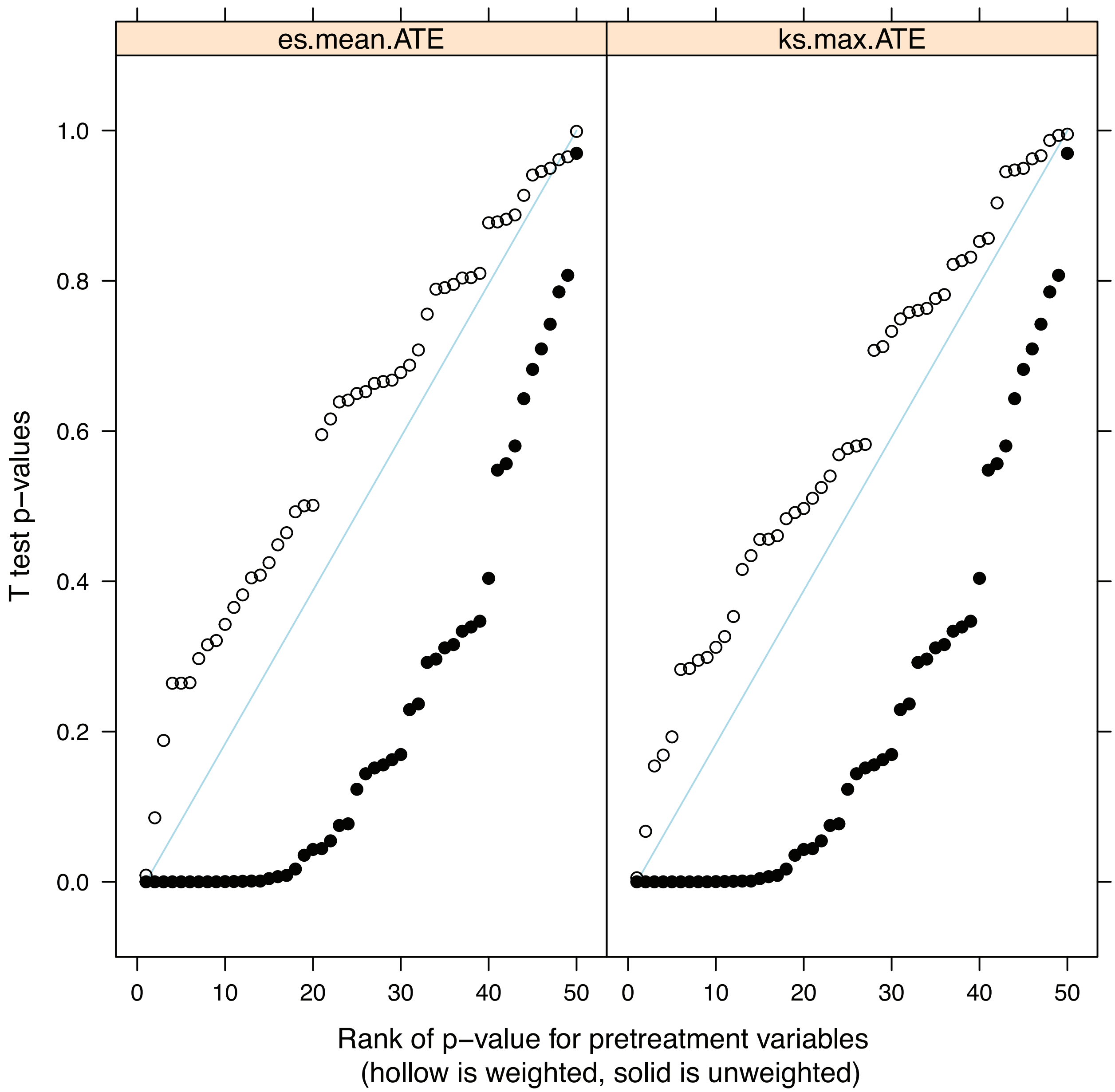

Figure 4 — Rank of p-value for pretreatment variables (solid is unweighted, hollow is weighted)

10 — Appendix B: Robustness Tables

Table 11 — Participant Effects with Controls [Weighted]

Outcomes	b	t-stat	p	q
Arts Work (y/n)	0.0313***	4.36	0.000	.001
Arts-Related Work (y/n)	0.0484***	2.93	0.003	.004
Non-Arts Work (y/n)	-0.0537***	-2.97	0.003	.004
Arts Work (Hours)	3.6471***	5.46	0.000	.001
Arts-Related Work (Hours)	0.3297	0.67	0.505	.254
Non-Arts Work (Hours)	-2.6877***	-4.46	0.000	.001
Arts Work (Earnings)	-6827.68	-0.74	0.462	.254
Arts-Related Work (Earnings)	-864.02	-1.00	0.318	.190
Non-Arts Work (Earnings)	-4137.64***	-3.19	0.001	.002
All Work (Earnings)	-11829.35	-1.21	0.227	.150

Note: *, **, *** indicate p-values < 0.1, 0.05, 0.01, respectively.

Table 12 — Results for Participants from SEM [Weighted]

Outcomes	b	p	q
Arts Work (y/n)	0.0309***	0.000	.001
Arts-Related Work (y/n)	0.0477***	0.004	.005
Non-Arts Work (y/n)	-0.0534***	0.003	.004
Arts Work (Hours)	3.4677***	0.000	.001
Arts-Related Work (Hours)	0.1483	0.775	.415
Non-Arts Work (Hours)	-3.0877***	0.000	.001
Arts Work (Earnings)	-7229.78	0.450	.250
Arts-Related Work (Earnings)	-1038.23	0.247	.141
Non-Arts Work (Earnings)	-4555.35***	0.001	.002
All Work (Earnings)	-12823.37	0.205	.133

Note: *, **, *** indicate p-values < 0.1, 0.05, 0.01, respectively.

Table 13 — Results for Participants from SEM of LASSO-Specified Equations [Weighted]

Outcomes	b	p	q
Arts Work (y/n)	0.0312***	0.000	.001
Arts-Related Work (y/n)	0.0478***	0.003	.004
Non-Arts Work (y/n)	-0.0545***	0.002	.003
Arts Work (Hours)	3.5712***	0.000	.001
Arts-Related Work (Hours)	0.2340	0.648	.350
Non-Arts Work (Hours)	-2.9691***	0.000	.001
Arts Work (Earnings)	-8430.05	0.441	.244
Arts-Related Work (Earnings)	-921.13	0.311	.185
Non-Arts Work (Earnings)	-4411.32***	0.002	.002
All Work (Earnings)	-13596.39	0.235	.156

Note: *, **, *** indicate p-values < 0.1, 0.05, 0.01, respectively.