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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February 4, 2025

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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

Scholars argue that the nature of artistic work can be unique from other occupations, such that these workers supply labor to multiple markets not always in their primary artistic occupation (Throsby 2007). In a traditional labor supply function, wages are typically a main factor. Throsby1994, however, models artists' labor supply as a function of both pecuniary and nonpecuniary benefits, such as the personal satisfaction that comes along with arts work. With this model, he posits that a traditional labor supply model might not apply to artistic occupations and we might see differing labor supply outcomes in response to different factors.

Several studies have tested Throsby's 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 are, on average, more satisfied with their work compared to non-artists, which supports Throsby's hypothesis that artists derive intrinsic utility from their artistic labor. These studies also find that differences in income, working hours, and personality do not fully explain the higher job satisfaction among artists. Another test of the model is through examining artists' time allocation decisions between arts work and non-arts work. Robinson and Montgomery2000 find that artists respond to economic incentives on the margin, supporting the "weak" version of the work-preference model, where artists adjust their labor supply based on external factors, but do not maximize total arts time. Bille's(2017) and Casacuberta and Gandelman's(2012) findings suggest that different forms of income, including non-labor income, have complex effects on artists' time allocation. The research further highlights the need to consider multiple income sources, such as royalties, temporary income, and non-market income, when modeling artistic labor supply.

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. 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. 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. 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, and the Saint Paul Guaranteed Income for Artists pilot, which offered $500 monthly payments to local artists to support their ongoing creative work. 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. These programs, like CRNY's, aimed to provide financial stability and empower artists to continue their practice despite economic challenges.

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.

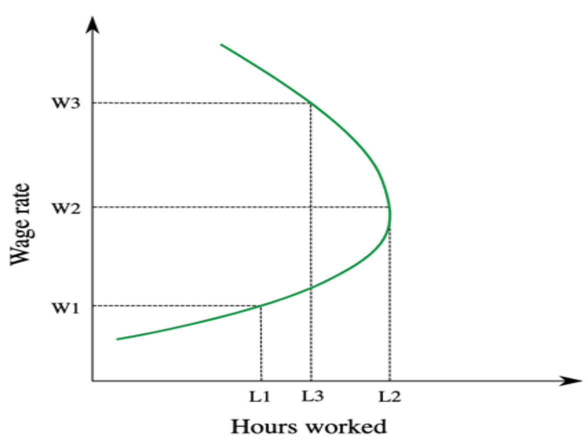

Figure 1 — Traditional Labor Supply Curve

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).

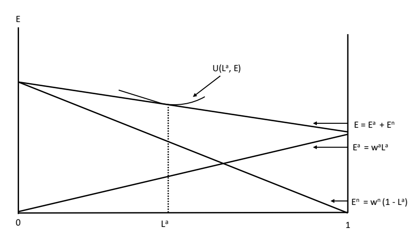

Figure 2 — Weak Version of Work Preference Model

Papandrea and Albon (2004) offer a model that highlights another common feature in artistic labor markets: the "arts pool" of artists searching for arts work while working in non-career work for low pay. Their model builds off of Throsby (1994) to show how psychic income essentially drives a wedge between equilibrium wages in arts and non-arts markets. Figure 3 comes directly from Papandrea and Albon (2004) and illustrates the equilibrium conditions of artistic labor supply. In their model, artists receive a psychic wage w_s from arts work in addition to pecuniary wages. The equilibrium *E* is defined by equating the marginal value product of labor in the non-arts sector (M_n) to that of the arts sector ($M_a + w_s$). Further, N_a is the number of artists employed in the arts and $w_n(1-\Lambda)$ is the number of artists employed in non-arts sectors. At *E*, artists are indifferent between arts wages (and the psychic income) or non-arts wages.

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. Studies such as Painter and Smith (2022), which investigated the Alaska Permanent Fund, 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. *Enrollment and Benefits Counseling*

To help ensure that participants could benefit from the program without jeopardizing their existing public assistance, CRNY offered benefits counseling. CRNY partnered with two organizations experienced in providing benefits counseling for low-income individuals: Henry Street Settlement, serving NYC-based artists, and Work Without Limits, supporting artists across the rest of New York State and those receiving SSI regardless of location. This counseling was particularly relevant for artists receiving benefits like Supplemental Security Income (SSI), Medicaid, or the Supplemental Nutrition Assistance Program (SNAP). Benefits counseling provided participants with information on how their guaranteed income payments could impact their eligibility for these services and helped them navigate the complex interactions between the GI payments and public benefits. Some participants, such as SSI recipients, faced specific challenges due to income limits imposed by public benefits programs. To address these issues, CRNY provided tailored solutions, including lump sum payments for 17 participants, which helped them avoid breaching monthly income limits that could have led to a reduction in their benefits. Among eligible applicants, 32 percent disclosed they were enrolled in public benefits. Of that group, 56 percent opted for benefits counseling, and 99 percent of those proceeded to enroll in the program, even though some of their benefits were or could be affected.

3.4. *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.*

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. (See Table 1.) 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 demographics, geographic location, priority factors, financial safety net questions, income, and artistic practice. These data were primarily used to select eligible applicants based on the priority criteria outlined above. In total, the application data contains information on 21,921 individuals.

Table 2 — Applicant Demographic Characteristics (unweighted)

Variable	N	Mean	std. dev.
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
Age: years	21920	35.736	12.474
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 3 — Applicant Artistic Characteristics (unweighted)

Variable	N	Mean	std. dev.
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 2 summarizes the demographic characteristics of the New York State artists applying to the GIA program. Table 3 summarizes the measures related to their artistic practices. The first nine variables in Table 2 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. 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. The top-listed artistic disciplines

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

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 were selected 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. The Wave 1 survey was administered 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

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)

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 again administered 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 and previously validated instruments (e.g., Throsby and Petetskaya 2024). The questionnaire was nearly the same for enrolled artists and control group artists.

4.3. Labor Market Outcome Measures

To measure the labor supply impacts of guaranteed income, this analysis uses several indicators from the survey. Time spent on work is measured both as a dummy variable to indicate labor-force participation and as an intensity measure that captures weekly hours of labor supplied (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 4 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 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.[3]

Table 4 — Descriptive Statistics for Labor Supply Measures

Variable	N	Mean	std. dev.
Participation - arts work	5353	0.948	0.221
Participation - arts-related work	5350	0.722	0.448
Participation - non-arts work	5343	0.708	0.455
Hours - arts work	5699	20.283	19.030
Hours - arts-related work	5699	9.955	13.674
Hours - non-arts work	5699	14.865	17.931
Earnings - arts work	5699	20825.79	586390.80
Earnings - arts-related work	5699	8210.42	30375.67
Earnings - non-arts work	5699	13172.25	54652.50
Earnings - total	5699	42208.47	616000.00

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

3. 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.

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 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.

5.1. Sample Weighting

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.

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 2 and Table 3.)

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 2 and 3 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 2 and 3. 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 5 and 6 illustrate the covariates used in the weighting process, now 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 in the Appendix 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 in the Appendix 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.

Tables 5 and 6 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 5 and 6 reflect this imbalance in sample characteristics for many covariates. The priority criteria determining the weighted lottery (shaded rows in Table 5) 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 5 — 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 6 — 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.

5.2. 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,[4] 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-

4. 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 2 and 3) 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 7, 8, and 9 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 7 — Impact of Guaranteed Income on Time Spent on Work

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 8 — Impact of Guaranteed Income on Hours Spent on Work

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.

Table 11 reports the heterogeneous impacts of guaranteed income on different categories of individuals, broken down by sex, age, caregiving status, BIPOC racial group, commercial art discipline (e.g., design, film, media, music), part-time (PT) status, college degree status, and location (NYC). The positive effects of guaranteed income on arts work participation are stronger for caregivers. Hours spent on arts work also increased more for graduates. No significant heterogeneity in impacts was found on for other groups.

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 9 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 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 9 — Impact of Guaranteed Income on Annual Earnings

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.

6.3. Heterogeneity

The heterogeneity analysis offers an initial exploration into possible differential effects of the cash transfer across groups. Table 10 shows the t-statistics for the interaction terms across an array of groups for each of the outcome variables. Holistically, very little heterogeneity is evident either for a particular group type or a particular outcome. Caregivers were more likely (than non-caregivers) to indicate working in the arts. The positive treatment effect on hours of arts work is smaller for artists with college degrees. Conversely, the negative treatment effect on non-arts earnings is mitigated for women (i.e., the earning reductions are driven by non-women). Otherwise, the estimated treatment effects do not appear to vary by age, race, or living in New York City. Further, effects do not differ by initial work conditions – part-time worker or practicing a more commercially oriented discipline like film or music.

Table 10 — Heterogeneous Impacts (t-statistics)

	Man	Woman	Old	Young	Care	Race	Commercial	PT	Grad	NYC
Arts Work (y/n)	-0.82	1.68	-1.51	-0.65	***2.54***	-0.12	-0.39	-0.81	-0.67	-1.20
Arts-Related Work (y/n)	-0.16	-0.11	0.29	-0.07	1.45	-0.05	0.53	-1.35	0.34	0.12
Non-Arts Work (y/n)	0.01	0.27	-0.24	0.69	0.10	0.03	0.32	0.12	-1.17	-1.40
Arts Work (Hours)	-0.12	0.06	-0.70	0.32	0.51	-0.12	0.38	-0.48	***-2.69***	-1.61
Arts-Related Work (Hours)	0.07	-0.08	0.26	0.14	0.61	1.05	0.93	-1.09	-0.28	1.00
Non-Arts Work (Hours)	-0.42	0.99	-1.10	-0.02	0.15	0.85	0.32	-0.72	-0.10	-1.52
Arts Work (Earnings)	1.25	0.73	0.93	1.12	-1.04	0.82	1.13	1.15	0.51	1.03
Arts-Related Work (Earnings)	0.34	0.60	1.33	0.14	-0.68	1.21	0.01	-0.05	-1.03	1.06
Non-Arts Work (Earnings)	-0.52	***2.40***	0.20	-0.49	-0.40	0.22	-0.22	-0.46	1.15	-0.48
All Work (Earnings)	1.14	1.07	1.25	1.00	-1.05	0.88	1.04	1.01	0.69	0.99

Note: t-statistics shown. For p<0.05, values are ***boldfaced and italicized***.

These 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. 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 LASSO-specified models estimated as simultaneous equations (Table 13) suggests that the additional controls and robust estimation change little. 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 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 highlight the need for comprehensive policies that integrate non-labor income with broader economic support to foster both artistic and financial sustainability.

This study also raises broader questions about the role of guaranteed income in addressing systemic inequities in the arts sector. The CRNY program's targeted approach, which prioritized artists from marginalized communities, highlights how guaranteed income can serve as a tool for promoting equity and inclusion in creative industries. Further, the program's large scale, relative to other GI pilot programs, enables an assessment of differential impacts for groups of participants. The reductions in earnings and shifts in career development outcomes, however, underscore the complexity of designing policies that balance immediate financial relief with long-term career sustainability.

More specifically, this analysis can inform expectations about the implications of a GI policy for the creative sector. In addition to advocating for a GI policy from with the arts, others have proposed GI as response to labor market impacts of pervasive artificial intelligence (AI) tools. The recent introduction of generative AI tools (e.g., ChatGPT, DALL-E, Midjourney) has been met with resistance and great concern from many in the creative workforce, seeing these AI tools as potentially effective substitutes for artistic labor in an already precarious market. If, simply put, generative AI takes human artists' jobs, and GI is used to support those displaced by AI, then CRNY's project can go a long way to informing how artists react to a guaranteed income. In terms of their labor market participation, 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.

In conclusion, the CRNY Guaranteed Income for Artists program demonstrates the potential of guaranteed income to enable artists to focus on their creative work and experiment with new ideas, while also highlighting trade-offs in earnings. These findings provide valuable insights for policymakers and advocates seeking to support the creative workforce and suggest that guaranteed income, when combined with complementary programs, can be a powerful tool for fostering creativity, equity, and economic stability in the arts sector.

In terms of future research, the large variance in estimated impacts on earnings, coupled with the short-term impacts being measured here, suggest that many artists do see positive (net) income impacts and many may experience long-term earnings increases. Long-term monitoring is necessary to understand these career and lifecycle impacts. Future research should continue to explore these types of long-term impacts on creative professionals, as well as its potential applications in other industries and contexts.

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A — Balancing Diagnostics

Appendix

Standardized Effect Sizes Pre/Post Weighting

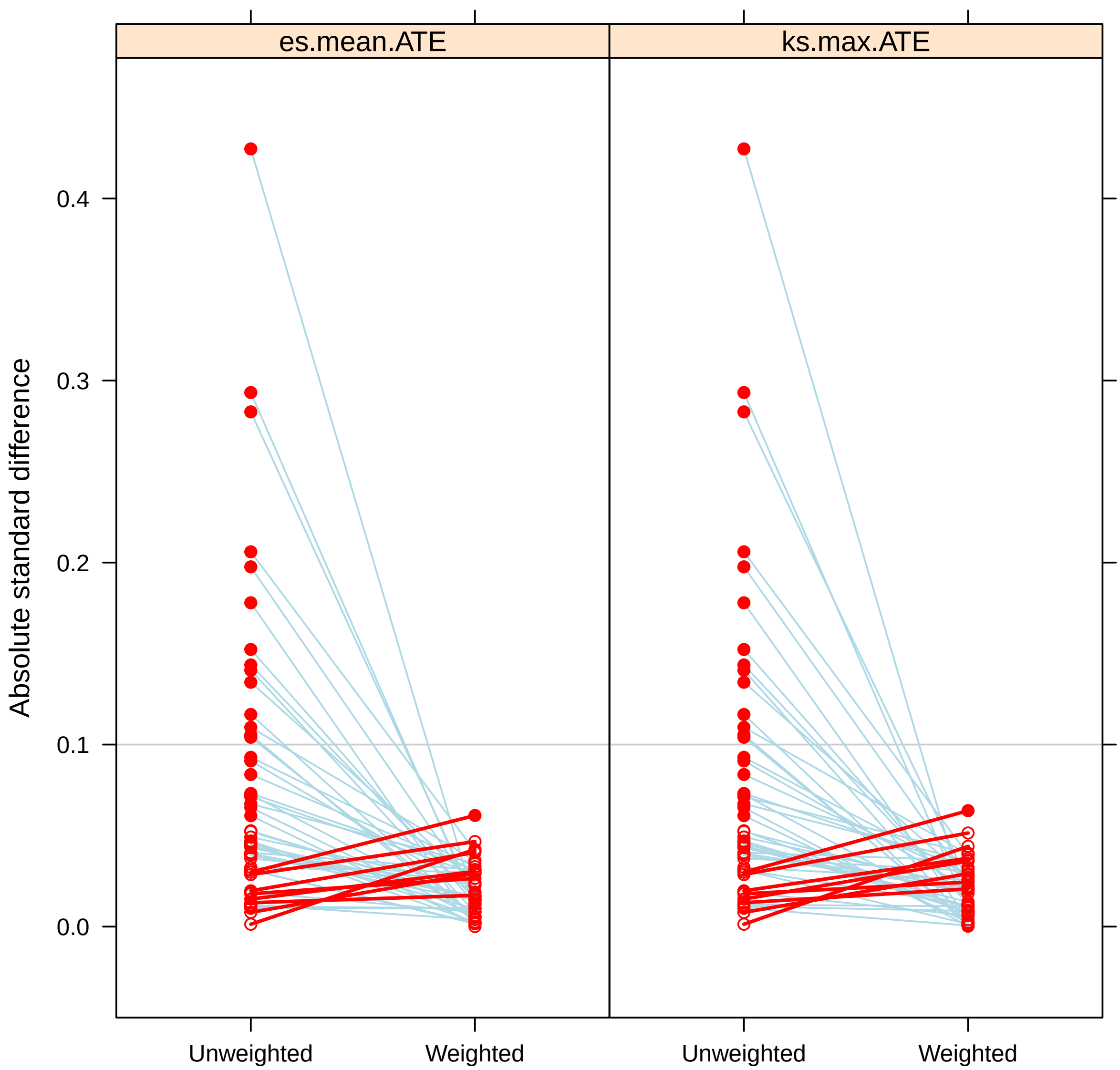

Figure 3 — Effectiveness of GBM weighting in balancing covariates, for two alternative stopping rules.

T-test P-values of Group Means of Covariates

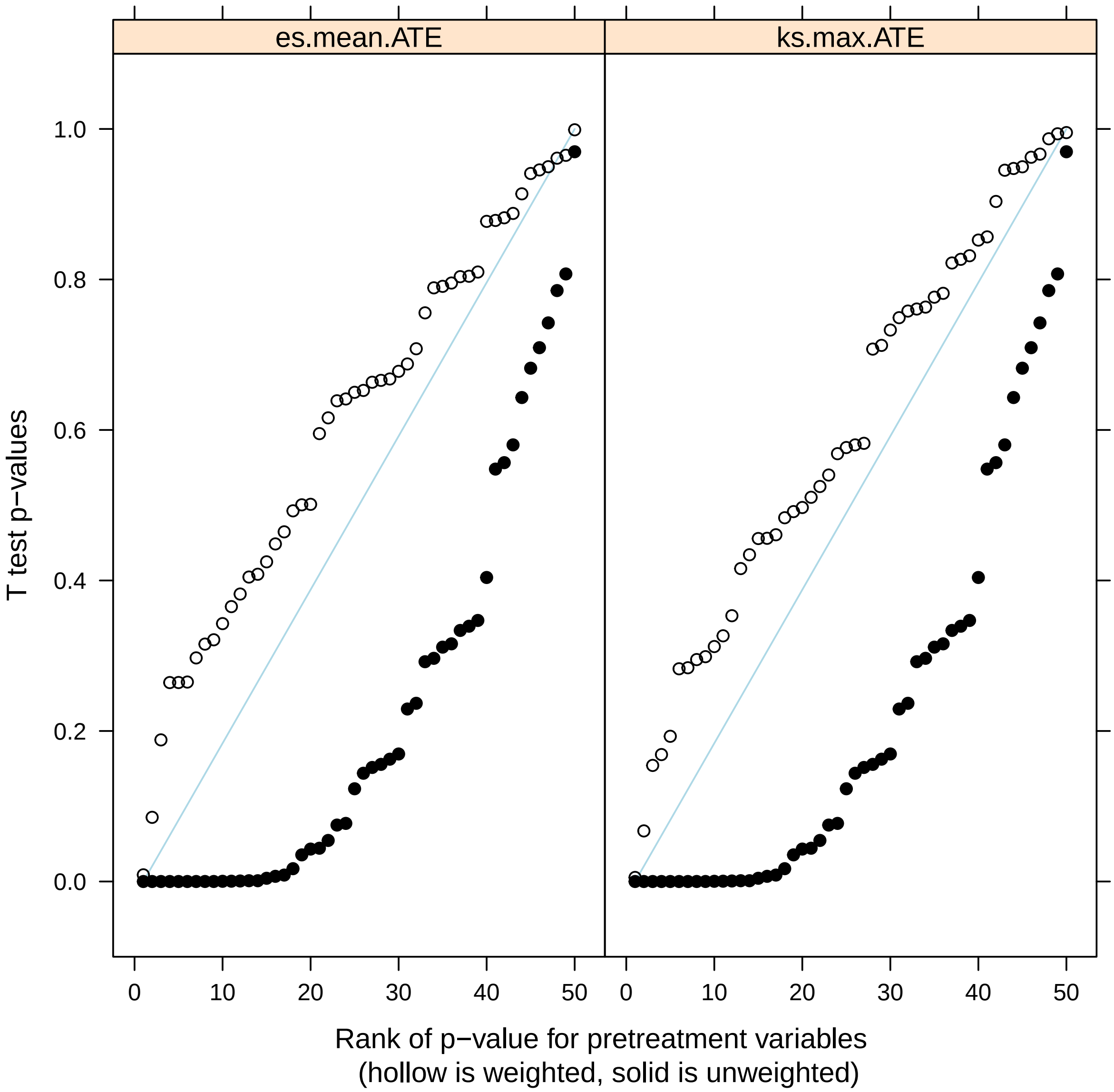

Figure 4 — Rank of p-value for pretreatment variables (solid is unweighted, hollow is weighted)

B — Data Appendix

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.