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Letter from the Editor

The Ashoka University Economics Review (AUER) is a culmination of our efforts and commitment to fostering undergraduate research in economics, coupled with interdisciplinary explorations of the discipline at Ashoka. We are delighted to unveil the fourth volume of the AUER, a compilation of high-quality, engaging manuscripts that traverse across various fields of economics and uphold the rigorous standards of economic research.

Our gratitude extends to the Department of Economics for their unwavering support in the realization of the AUER. All our endeavours this year wouldn't have been nearly as successful as they were if it were not for our Managing Editor, *Shagun Khetan*, and our dedicated team of editors, *Aditya Kumar, Aditya Patnaik, Riya Nagar, Rohan Wagle, Yasashvi Paarakh, and Yash Khaitan.* Their efforts, engagement, and commitment to our workshops and refining and reviewing the manuscripts that grace these pages have made this journal what it is.

The journal's inaugural paper investigates the intricate relationship between the adoption of UPI payments and crime through a quasi-natural experiment. The paper makes a compelling case for the positive externalities of financial inclusion and speaks directly to policymakers navigating the twin challenges of digital transformation and public safety. The second paper turns to a question of equal urgency: how do community food programs shape women's labour force decisions? The authors explore the gendered nature of time use and its effects on decision-making in the labor market. The third paper takes on a more analytical challenge: deriving and validating a simplified, intuitive complement to the Atkinson Index of inequality. The fourth paper navigates how equity wealth shapes household spending across developed and developing contexts.

We hope this volume not only provides a thought-provoking read but also encourages more undergraduates to engage with economic research more meaningfully and to question more critically. By welcoming work from a range of perspectives and methods, we aim to make a meaningful contribution, however modest, to the growing body of economic literature. I can only hope that this journal and our presence on campus encourage more Ashokans to engage and explore the many facets of economics at Ashoka more critically and intentionally.

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Can Digital Payment Adoption Reduce Crime?: Empirical Evidence from India

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Abstract

The introduction of Unified Payments Interface (UPI) in 2016 transformed the digital payments landscape in India. We utilize district-level variation in UPI adoption through differential timings of district 'lead banks' joining the UPI platform to study the effects of digital payments on crime. We employ a Difference-in-Difference strategy to test our hypothesis that UPI adoption is negatively associated with the incidence of economic crimes such as robbery and burglary. We explain our hypothesis through the channels of decreased cash availability and an income effect. Our results show that treatment districts which adopted UPI earlier experienced lower economic crime but had no difference in non-economic crime compared to their control counterparts. Robustness tests which restrict our sample to districts with higher mobile ownership show an even greater decrease in crime, providing support for hypothesized channels. Our research contributes to the literature examining the social and developmental consequences of financial inclusion and digital payments.

Keywords: UPI, economic crime, lead bank, robbery.

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1 Introduction

In 2016, the *National Payments Corporation of India* (NPCI) launched the Unified Payments Interface (UPI)— a real-time payment system facilitating inter-bank peer-to-peer and person-to-merchant transactions. The system operates through any UPI client mobile application, where users can link multiple bank accounts and transfer or request funds using their unique UPI ID and registered mobile number. With 622 banks offering UPI services and 16 billion transactions amounting to 23.5 trillion rupees in October 2024 alone (NPCI 2024), UPI has made India a leader in the digital payments ecosystem.

Our paper is set against the backdrop of this increasing UPI uptake as well as demonetization— where the Government of India removed the legal tender status of notes of denomination Rs. 200 and Rs. 500 in an attempt to counter 'black money' and the shadow economy. We specifically explore the effect of UPI uptake on crime. There was a pilot launch of UPI in 2016 and this coincided with the timeline for demonetization. Motivated by the findings of Zhao and Huang (2023) investigating the relationship between mobile payments and crime in China, this paper seeks to explore whether districts with a higher UPI uptake have lower rates of crime, specifically economic crime.

We use a Difference-in-Difference design to study this hypothesis. It is inspired by the work of Dubey and Purnanandam (2023) who classify districts into two groups - early and late adopters - based on whether the 'Lead Bank' in a district, ascertained by the *Reserve Bank of India* (RBI), was an early adopter of UPI. This helps us create two groups of control and treatment. This decision by banks is taken at the national level so, it is unlikely to be correlated with specific district characteristics, making the assignment quasi-random. We measure the outcome of crime, specifically economic crimes— robbery, burglary and theft— in pre and post periods, with robbery as our main outcome of interest.

As hypothesized, we find a negative impact of UPI uptake on crime. Parallel pre-trends hold for robbery and burglary and both have negative coefficients. Districts which are early adopters

of UPI (treatment group) have on average -0.43 fewer robberies per lakh[2] population in the post period than the expected mean change. This result is economically significant since it represents a 17.9% reduction in robberies from the pre-period sample mean. The fact that the effect is negligible on the non-economic crime of murder further strengthens our hypothesis that this reduction is due to changes in economic and financial variables.

We also run a robustness check by restricting the sample to districts with high mobile penetration (75th percentile and above). These districts will have a higher uptake of UPI and hence should see a higher negative effect on the rate of economic crime. We find that this is indeed the case. The coefficient for robbery in this case is -1.24 as compared to -0.43 in our results and it becomes statistically significant at the 1% level. Additionally, the burglary coefficient becomes significant at the 5% level.

We attribute these results to two primary channels: an increase in formal savings which decreases cash holdings and an increase in income. Bachas et. al (2021) find that providing debit cards increases savings (overall and formal) through channels of reduced transaction costs and increased trust due to regular bank balance validation. We hypothesize these channels to hold true in the case of UPI as well. Informal savings are increased and cash holdings are reduced which reduces economic crime (Armey et al. 2014). Dubey and Purnanandam (2023) find income effects of increased digital payments (adoption of UPI). This increased income leads to an 'income effect' that reduces crime (Becker, 1968). We substantiate these channels further in the literature review section.

Demonetization is an important phenomenon to be considered in our results. We find that post-demonetization, economic crimes in districts increased due to the impact it had on reducing household savings (due to the high conversion costs) and household incomes (Krishnan et al. 2017). This effect is however counteracted by the positive effects of UPI in treatment districts that overall, decreases economic crime. Hence, we see differential trends in crime in our con-

[2] 1 lakh = 1,00,000

trol and treatment districts in the post-period.

Our paper is relevant for policymakers because it examines the positive externality associated with UPI adoption. The fact that it is an externality related to crime is all the more important because of the immense economic impact of crime. Some measures find that the cost of crime is about 2% of the USA's GDP (Chaflin 2015). In a developing country like India, these costs and the cost of controlling crime can be higher. Additionally, crime is an understudied topic in the Indian context even though it is an important determinant of standard of living. Economic crimes also affect efficient allocation of resources, investment flows and economic vitality of small businesses. Our paper adds to the literature across these strands and highlights the (positive) unintended consequences of policy.

2 Background

This paper is set against the background of expanding UPI adoption and demonetization. There has been a push for UPI adoption by the Government of India, after its pilot launch in April 2016. Firstly, every Indian resident received a unique identification card, the Aadhaar Card, as part of a nationwide initiative beginning in 2010. Subsequently, Pradhan Mantri Jan-Dhan Yojana (JDY), a universal banking program aimed at granting a bank account to every household in the nation (Chopra et. al. 2017) was rolled out in 2014. Thirdly, significant resources were allocated to develop the necessary digital infrastructure for a secure and efficient payment system spanning multiple platforms (Acharya 2023). In addition to this development of digital infrastructure, various advertisement campaigns were rolled out to increase adoption. Demonetization in 2016 is a significant event in the context of our paper. It affects both UPI adoption and crime. It positively affects UPI adoption while negatively affecting crime which affects our results (detailed analysis in the discussion section). Moreover, economic crime also remained high with a PricewaterhouseCoopers (PwC) report published in 2016 finding that 31% of respondents from India reported having experienced economic crime in the past 2 years.

2.1 Literature Review

Our paper is motivated by the findings of Zhao and Huang (2023) who present evidence on the relationship between mobile payments and crime in China. A 2016 policy change in China created a national-level expansion in mobile payments. Utilizing the variation in mobile payment usage across prefectures, Zhao and Huang compare crime-related outcomes through a difference-in-differences empirical strategy. They find that increases in mobile payments have significant negative impacts on crime. Specifically, they distinguish between economic crimes such as theft, burglary and robbery and non-economic crimes such as homicide, finding that the intensity of digital payment usage is effective only in reducing economic crimes but has zero effects on non-economic crimes. Their results show that in regions more exposed to digital payments, the number of criminal cases of theft per 10,000 inhabitants decreased (on average) by roughly 15% of the sample mean. The authors explain these significant findings through the primary channel of 'decreased cash holdings' resulting from an increase in mobile payment usage. Individuals prefer to place their income in formal savings institutions such as banks in order to utilize mobile payment systems, therefore reducing the cash kept on-person or in their private properties. This reduces the expected returns from crimes such as theft, robbery and burglary and hence, reduces the incidence of economic crime. Using this literature as motivation we partly explain our findings through the cash channel.

Bachas et al. (2021) find that a scheme that provides debit cards to cash transfer beneficiaries (who own bank accounts) increases both overall and formal savings. The two channels identified for these results are decreased transaction costs and reduced indirect costs of checking bank balances. In essence, the large networks of ATMs reduce the transaction costs of accessing money once deposited into banks and hence increases formal savings. Secondly, the reduction in indirect costs of checking bank balances enables individuals to verify that banks are not unexpectedly reducing balances, creating trust in the banks and banking systems. These channels, especially the former, are relevant to UPI. In a country like India with a large population and geographical variation, the average distance to a bank branch is high. UPI payments facilitate ease in transactions as individuals do not have to go to bank branches to transact. It

also reduces the speed of transactions. With regards to the latter channel, UPI apps like Paytm, PhonePe, Google Pay, etc. have a feature where an individual can check their bank balance. While this feature can lead to increased trust in banks, it cannot be claimed with certainty ex-ante as the adoption of UPI itself can be driven by a channel of trust, leading to reverse causality and self-selection bias. The overall increase in formal savings results in less cash being stored at homes, in-person and in circulation within the economy.

Various studies have established a link between cash and crime. Wright and co-authors (2017) find that a reduction in the circulation of cash via an Electronic Benefit Transfer reduces overall crime rate by 9.2%. They also note that the overall decrease in crime in the United States coincides with periods of decline in the proportion of financial transactions in cash. In our paper, the reduced volume of cash reduces the risk of crimes like robbery, burglary and theft. Armey et al. (2014) revealed a significant association between electronic payments and reduced economic crimes such as robbery and burglary but find limited impact on non-economic crimes like homicide and rape. We similarly examine the effect on these economic crimes as compared to non-economic crimes like murder to examine the strength of our cash channel, since reduced cash in circulation should ex-ante not have any impact on a crime like murder which is usually committed for alternate reasons. Increased cashless transactions also have a dampening impact on crimes like corruption as explored by Setor et al. (2021). However, we limit our analysis to economic crimes reported in the National Crime Records Bureau database (which excludes corruption) due to a lack of reliable reporting.

Dubey and Purnanandam (2023) find income effects of increased digital payments (adoption of UPI). A doubling of digital payment leads to 6.2% higher income. According to economic theory, this 'income effect' reduces the economic incentive for crime (Becker, 1968). This effect of UPI adoption is our second channel that leads to a decrease in crimes. Thus, a combination of economic effects namely increased (formal) savings and income results in lower economic crimes.

This leads to the natural question: why study the effect of UPI on crime and not on these economic outcomes? We choose to study the impact on crime firstly, because crime itself has large economic costs, especially in developing countries. Substantiating the economic effect of crime, Detotto and Otranto (2010) likened it to a tax on the economy that reduces domestic and foreign investment, creates inefficient allocation of resources and reduces a firm's competitiveness. By some measures, in the United States, the cost of crime, narrowly constructed, is about 2% of GDP while other measures find it to be 6% of GDP (Chaflin 2015). In addition to the direct economic consequences of crimes, there is also significant spending on crime control.

If the link between UPI uptake and crime can be established, it can lead to more informed policy decisions on the subject. Additionally, crime itself is an understudied topic in India. Studying it as an externality, or an unintended consequence of a policy (UPI uptake) is novel and deserves its own strand of research. We believe that our results are relevant to economies facing the twin phenomenon of high levels of crime and greater adoption of digital payments. A relationship between these two phenomena shows evidence of the supporting role that financial inclusion (through digital payments) plays in deterring crime and improving developmental outcomes. With the advent of UPI in 2016, India's economy has undergone a major digital payments revolution. Alongside its economic implications, the effect of UPI on social and developmental outcomes, like crime, is a relevant and necessary area of research.

2.2 Data and Descriptive Statistics

Our outcome crime variables — robbery, theft, burglary and crime — are obtained from the 'Crime in India' report released by the National Crime Records Bureau (NCRB) every year, which provides district-level data on all crimes booked under the Indian Penal Code. To account for socioeconomic factors and population demographics, we collect data at the district level from the 2011 Census. Since there are discrepancies in district names and boundaries in the NCRB dataset and the 2011 Census, we use data downloaded from Ashoka University's *Centre for Economic Data and Analysis* (CEDA) Data Portal which contains crime data matched to census districts. These variables are defined in Table 1 and their summary statistics

are provided in Table 2.

Table 1: Definition of variables

Variable	**Definition**	**Data Sources**
theft	Number of theft cases (as per IPC section 390) per lakh population in a district	NCRB (through CEDA Data Portal)
robbery	Number of robbery cases (as per IPC section 390) per lakh population in a district	NCRB (through CEDA Data Portal)
burglary	Number of burglary cases (as per IPC section 443) per lakh population in a district	NCRB (through CEDA Data Portal)
murder	Number of murder cases (as per IPC section 302) per lakh population in a district	NCRB (through CEDA Data Portal)
literate	Share of literate population in a district	Census 2011
ruralHHshare	Share of rural households in a district	Census 2011
mobileHHshare	Share of households in a district with mobile ownership	Census 2011
internetHHshare	Share of households in a district with internet access	Census 2011

Table 2: Summary Statistics by Districts with Early and Late UPI Adoption by Lead Banks

	Mean	**SD**	**Min**	**Max**	**N**
Early UPI Adopting Districts					
Theft	31.73	80.83	0.00	1615.42	815
Robbery	2.21	5.40	0.00	88.45	815
Burglary	6.38	7.82	0.00	86.23	815
Murder	2.49	1.82	0.00	17.06	815
Literate Population Share	0.64	0.10	0.40	0.89	815
Share of Rural Households	0.67	0.21	0.00	0.93	815
Share of Households with Internet	0.02	0.03	0.00	0.17	815
Share of Households with Mobile	0.39	0.09	0.16	0.58	815
Late UPI Adopting Districts					
Theft	35.74	115.42	0.00	2090.03	2325
Robbery	2.19	4.76	0.00	86.00	2325
Burglary	6.93	10.02	0.00	140.39	2325
Murder	2.52	1.58	0.00	34.08	2325
Literate Population Share	0.62	0.10	0.29	0.87	2325
Share of Rural Households	0.75	0.20	0.00	1.00	2325
Share of Households with Internet	0.01	0.02	0.00	0.17	2325
Share of Households with Mobile	0.36	0.10	0.01	0.63	2325
Total					
Theft	34.70	107.52	0.00	2090.03	3140
Robbery	2.20	4.93	0.00	88.45	3140
Burglary	6.79	9.50	0.00	140.39	3140
Murder	2.51	1.64	0.00	34.08	3140
Literate Population Share	0.62	0.10	0.29	0.89	3140
Share of Rural Households	0.73	0.21	0.00	1.00	3140
Share of Households with Internet	0.02	0.02	0.00	0.17	3140
Share of Households with Mobile	0.37	0.10	0.01	0.63	3140

Note: The crime variables (theft, robbery, burglary and murder) are cases per lakh population.

Source: Crime variables - NCRB sourced from CEDA. District Characteristics - 2011 Census

3 Empirical Strategy

Our identification strategy is motivated by Dubey and Purnanandam (2023) who study the impact of UPI adoption on household income and small business activities. Their novel strategy utilizes differences in the timing of participation on the UPI platform by different banks to establish a causal link between digital payments and economic outcomes. Our strategy is similarly based on the variation in the timing of exposure to UPI payments across districts based on when the 'lead bank' of a district decided to participate in the UPI system.

The 'Lead Bank' system was established by the Reserve Bank of India in 1969 on the recommendations of the Gadgil Study Group which provided plans to improve access to banking and credit structures in rural areas (RBI 2016). Due to a lack of commercial bank presence and orientation towards rural areas, these public-sector lead banks present in all districts are tasked with the objectives of improving banking access and financial services to underserved communities. Hence, the specific policies adopted by public-sector banks (eg. whether to participate in UPI) have significant effects on the extent and nature of financial inclusion experienced by the populations residing in the districts where the bank is the 'lead bank'.

When UPI was introduced in August 2016, 29 banks indicated their interest in joining the new platform. 21 of them joined the platform immediately, while the other 8 joined by the end of November 2016. However, within these 'early-mover' government banks, there were some which were notably missing from the list given their large market share. For customers of these banks, this posed a barrier to them adopting digital payments even if they wished to do so. By May 2017, even the other 'late adopter' banks had joined the platform.

3.1 Difference-in-Differences

Why do we not do a simple difference (pre-post 2016) to estimate the impact of digital payment adoption on crime? It could have been that people started using UPI in response to an increase in cases of theft/robbery/burglary and this implied reverse causality would lead to an

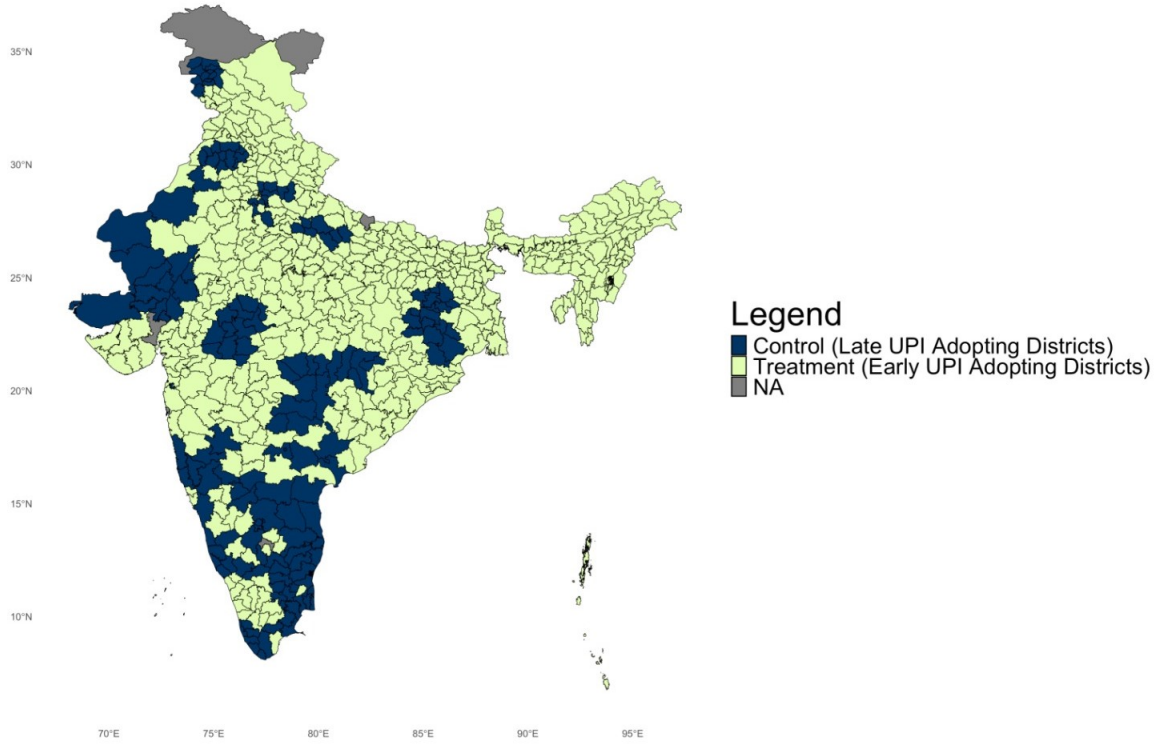


Figure 1: India Map showing Districts whose Lead Bank adopted UPI Early vs Late

exaggeration of our studied effect. To deal with such endogeneity issues, we use the differential adoption of UPI by lead banks as an exogenous policy 'shock' unrelated to crime but leading to variations in digital payment access across districts.

For our difference-in-differences method, we utilize variation in the timing of lead banks participating in the UPI scheme to construct our treatment group (which consists of districts that were early adopters) and control group (late adopters) to find the impact of UPI adoption on economic crimes such as theft, robbery and burglary. One of the main assumptions of our identification strategy is that the pre-trends in our crime rates of interest are 'parallel'. Thus, the changing differential in crime rates between treatment and control groups can be solely attributed to the UPI shock. We discuss parallel pre-trends and threats to this identification strategy in the next sections.

3.2 Estimating Equations

Our empirical specification to measure the difference-in-difference estimate is the following:

$$Y_{it} = \beta_0 + \beta_1 * Treat \times Post + \beta_2 * X_{it}^{'} + \mu_i + year_t + \varepsilon_{it} \quad (1)$$

Here i and t index districts and time respectively. Our outcome variable Y_{it} is different crime indicators like robbery, theft, burglary and murder in district i at time t. $Treat$ is a binary variable which takes the value 1 for early UPI-adopting districts and 0 for late adopters. $Post$ is also a dummy which takes the value 1 for years post 2016 and 0 otherwise. $X_{it}^{'}$ are our covariates, and ε_{it} is the error term. μ_i and $year_t$ are district-level and time-fixed effects, respectively.

The district-level fixed effects washes away all time-invariant differences across districts (for example: location of the district) in our sample while the time-fixed effects controls for factors which are constant across districts but vary over time (for example: national-level policies). Including these fixed effects is one reason why we can afford to have few covariates, and why the controls we have included may not show significant coefficients. This is also why we do not separately have the treatment and post dummies since these are differenced away.

The β_1 coefficient in Equation (1) can be interpreted as the Average Treatment Effect on Treated or the DiD estimate, after accounting for various controls and fixed effects. We expect the β_1 coefficient to be negative if our hypothesis, that the introduction of UPI payments reduced economic crime, stands true.

4 Results

4.1 Verifying Parallel Trends

Our figure 2 provides a visual representation of the trends for the robbery variable in the pre-period. Visually, parallel pre-trends can be observed for the period from 2014 to 2016 (pre-treatment year) providing evidence for the hypothesis of no differential growth rates of robbery for treatment and control districts. In the post-period, we can visually verify that the control group witnesses a change in growth rates (becomes stagnant and then rises) while the treatment

Table 3: Results of Parallel Trends Check

	(1) Robbery b/se
Treat × year=2014	-0.05
	(0.24)
Treat × year=2015	0.24
	(0.24)
Control Variables	YES
District Fixed Effects	YES
Year Fixed Effects	YES
Observations	1886

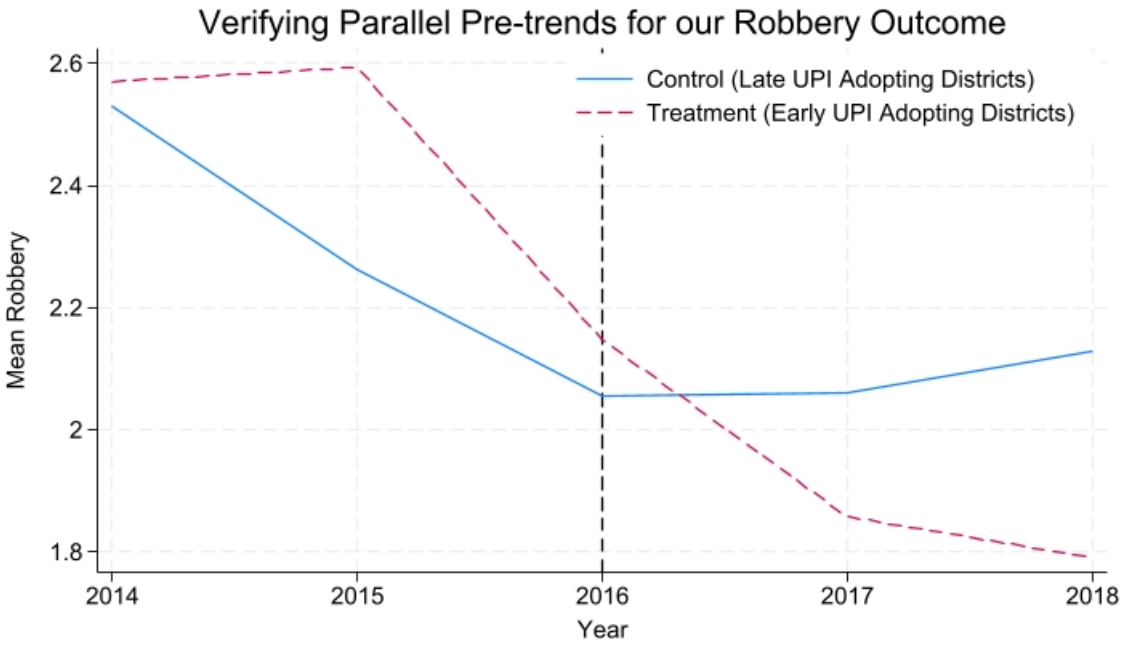


Figure 2: Parallel Trends

group witnesses a continued negative trend. In Table 3 we can see that the coefficients for the year (2014, 2015) interacted with treatment are statistically insignificant, verifying parallel pre-trends. Similarly, parallel pre-trends hold for burglary but not for theft and murder. (Can be visually ascertained from graphs in our appendix)

4.2 Baseline Estimates

Table 4: Estimated Effects of UPI adoption on Crime

	(1) Robbery b/se	(2) Robbery b/se	(3) Theft b/se	(4) Burglary b/se	(5) Murder b/se
Treat*Post	-0.43**	-0.43**	-1.08	-0.54	0.00
	(0.19)	(0.19)	(3.04)	(0.44)	(0.08)
Population		-0.00	-0.00	-0.00	-0.00
		(0.00)	(0.00)	(0.00)	(0.00)
Literate		0.00	-0.00	0.00	0.00
		(0.00)	(0.00)	(0.00)	(0.00)
Rural Household Share		-0.00	-6.40	0.77	-0.75
		(3.35)	(52.25)	(7.63)	(1.35)
Internet Household Share		-10.54	152.57	-97.57	5.94
		(170.32)	(2653.94)	(387.32)	(68.68)
Mobile Household Share		-3.84	38.05	6.32	1.72
		(9.75)	(151.91)	(22.17)	(3.93)
District Fixed Effects	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES
Observations	3140	3140	3140	3140	3140

Results in Table 3 show that the coefficient of the Treat*Post interaction terms when regressed on the outcome variable of Robbery is -0.43 and is statistically significant at the 5% level. This can be interpreted as: Districts which are early adopters of UPI (treatment group) have on average -0.43 less robberies per lakh population in the post period than the expected mean change. This result is economically significant since it represents a 17.9% reduction in robberies from the pre-period sample mean.

Our coefficient estimate for Treat*Post on the outcome variables of Theft (parallel pre-trends do not hold) and Burglary (pre-trends hold) retain the hypothesized negative coefficients but are not statistically significant. Its coefficient on the outcome variable of murder is 0 and hence,

shows a zero effect but is statistically insignificant.

The coefficient estimate for Treat*Post when regressed on robberies remains unchanged after the inclusion of control due to the presence of District-level fixed effects which capture all the time-invariant differences across districts.

4.3 Robustness

Table 5: Estimated Effects of UPI adoption on Crime - Districts with High Mobile Penetration

	(1) robberyrobust b/se	(2) theftrobust b/se	(3) burglaryrobust b/se	(4) murderrobust b/se
Treat*Post	-1.24***	8.86**	-2.29**	0.05
	(0.43)	(4.13)	(1.12)	(0.09)
District Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Observations	786	786	786	1878

We conduct a robustness test by running our DID only in districts with higher mobile penetration. According to 2011 census data, we choose districts above the 75th percentile (i.e. 45% of mobile penetration in a district). The argument is that UPI uptake will be higher in districts with higher mobile penetration. Hence, if UPI uptake is the channel of crime reduction, we should find a higher negative coefficient in these districts. Post analysis, we find that this is indeed the case. The coefficient for robbery in this case is -1.24 as compared to -0.43 in our results (Table 4) and it becomes statistically significant at the 1% level. This is a 41% reduction. This is quite significant but might be an overestimate given identification issues. Burglary has a larger negative coefficient which is statistically significant at the 5% level. The effect on murder continues to remain insignificant. The effect on theft is surprising as the coefficient increases and is significant. However, as reported earlier, parallel pre-trends do not hold for theft so the coeffcient is not relevant. Thus, we conclude that our results in terms of channels are verified through the robustness check.

A potential limitation we find in using this robustness strategy is that the data is 2011 data.

Trends in mobile penetration might have changed significantly since then. However, an argument could be made that lead districts would remain so in terms of mobile penetration.

5 Discussion

Our coefficient estimates in Table 4 for the Treat*Post variable show statistically significant results only for the Robbery outcome variable and not for other economic crimes of Theft and Burglary. We explain these findings as driven by our primary channel of 'decreased cash holdings' due to formal savings since robbery is motivated more by the availability of cash than crimes such as burglary. Theft is defined as the act or intention of dishonestly taking away another's private property and Robbery is theft while voluntarily causing harm to the victim. Burglary is the act of trespassing on privately owned real estate (Legislative Department). Burglary usually involves house theft of valuables such as expensive assets and metals and hence, is not expected to be motivated primarily by cash availability. This could potentially explain the statistical insignificance of our coefficient on burglary. Robbery on the other hand is more likely to be motivated by cash availability since it usually occurs in settings against individuals (as opposed to real estate).

Most importantly our results show a zero coefficient on Murder which supports our hypothesis that UPI adoption does not have any impact on non-economic crimes. Research shows that the drivers of murder are multifactorial and are caused by psychological, psychopathological, social and developmental factors (Bothelo and Goncalves 2016). Hence, our expectation of a weak or zero effect of UPI adoption (through income or cash channels) on murder is captured by our regression estimate.

The external shock of demonetization which occurred in 2016 adds a new dimension to our results. Demonetization had the impact of reducing household savings (due to the high cash conversion costs) and had a negative impact on household incomes (Krishnan et al. 2017). Through the literature surveyed in the literature review section, this wealth shock and lower

savings are correlated with a rise in crimes, especially economic crimes such as robbery, theft and burglary. However, since UPI uptake coincided with demonetization, it counteracted its effects in the treatment group. UPI's effect on increasing formal savings and income, subsequently reducing crimes counteracted the impacts of demonetization in districts that are early adopters of UPI. This phenomenon can be observed in Figure 2 since the negative pre-trend for the control group (late UPI adopters) stagnates (and then rises) while the negative trends for the treatment group (early UPI adopters) continue to hold in the post-period as well.

6 Limitations & Future Research

6.1 Threats to Identification

Our identification strategy is driven by classifying districts as early and late adopters based on whether the Lead Bank in the district was an early adopter of UPI or not. This involves two sets of assumptions that need not necessarily hold true. Firstly, it assumes that the lead bank alone (or largely) drives UPI adoption in a district. This might not be the case, especially in districts that have multiple banks such that other banks could be early adopters. In this case, these districts would be coded as late adopters and will bias our coefficients downwards. Secondly, this strategy assumes that if the lead bank is an early adopter then a significant proportion of the population would end up adopting UPI. However, this might not be the case. This means that districts we classify as early adopters are truly late adopters (based on population UPI uptake). This again biases our results downwards. While these are limitations of the identification strategy, they actually strengthen our claims. In this context, our coefficients are the lower bound estimates.

6.2 Other Limitations

Our paper is set against the backdrop of Demonetization. This is an external shock that affected both UPI uptake and crime. In the absence of the shock, it is difficult to claim what results would have been. It is possible that the differences would not be as stark. Additionally, demonetization had differential impacts across different districts that we have not been able to

account for. So, this paper might not be generalizable across different countries and economic contexts.

There are several limitations to using the NCRB crime data. Chaudhuri et al. (2014) acknowledge that crime may be severely under-reported. This leads to attenuation bias. However, if this under-reporting is differential across different districts then the impact cannot be predicted ex-ante.

6.3 Scope for future research

We identify two channels that lead to our results - increased formal savings (lower cash in circulation) and increased income. Though these effects of UPI are found in previous literature, future research could measure these channels along with impacts on crime on the same dataset and time frame to strengthen claims.

There is scope to do a heterogeneity analysis along the lines of intensity of UPI usage among different districts. Additionally, as mentioned in our literature review, cashless transactions affect crimes like corruption as well. Future research could examine other economic crimes like corruption as well, potentially creating an index of economic crimes.

7 Conclusion and Policy Implications

Our paper provides evidence of the association between the introduction of UPI technology in India in 2016 and a decrease in economic crime. These findings have important implications. As national payment systems proliferate across the world, it is important to consider the externalities brought upon by their introduction. For policymakers in the developing world, this evidence helps give impetus to encouraging technological innovation that targets multiple developmental goals like financial inclusion and personal security. Encouraging digital payments not only strengthens financial systems but also improves social welfare and trust (through reduced crime) which has significant positive externalities on the overall growth and development context of a country.

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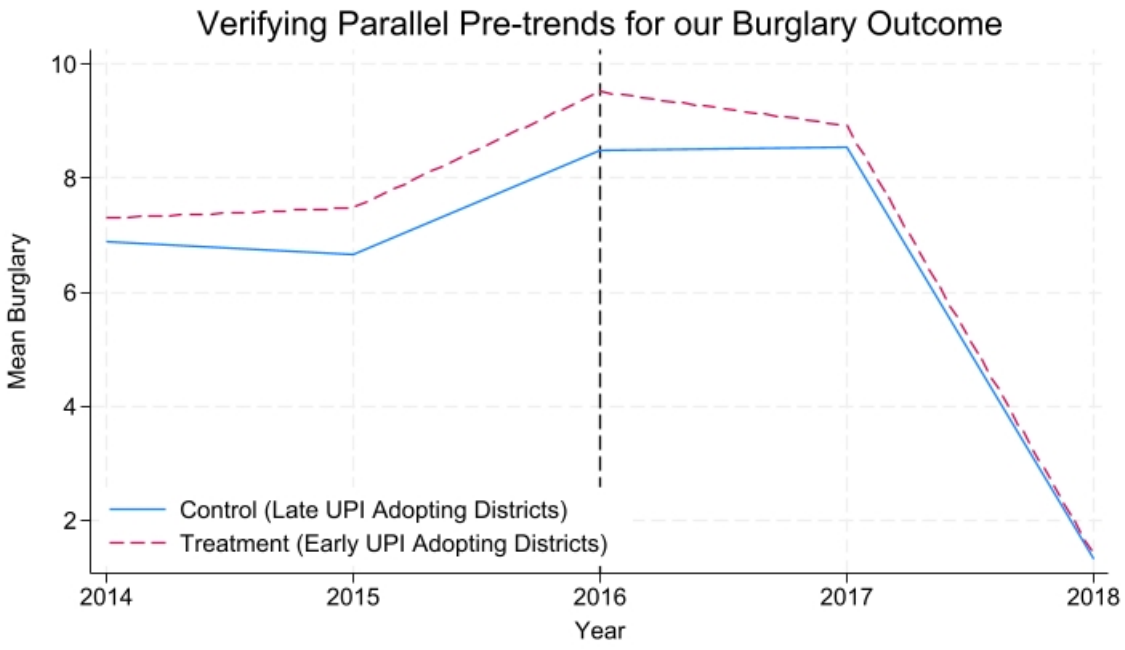
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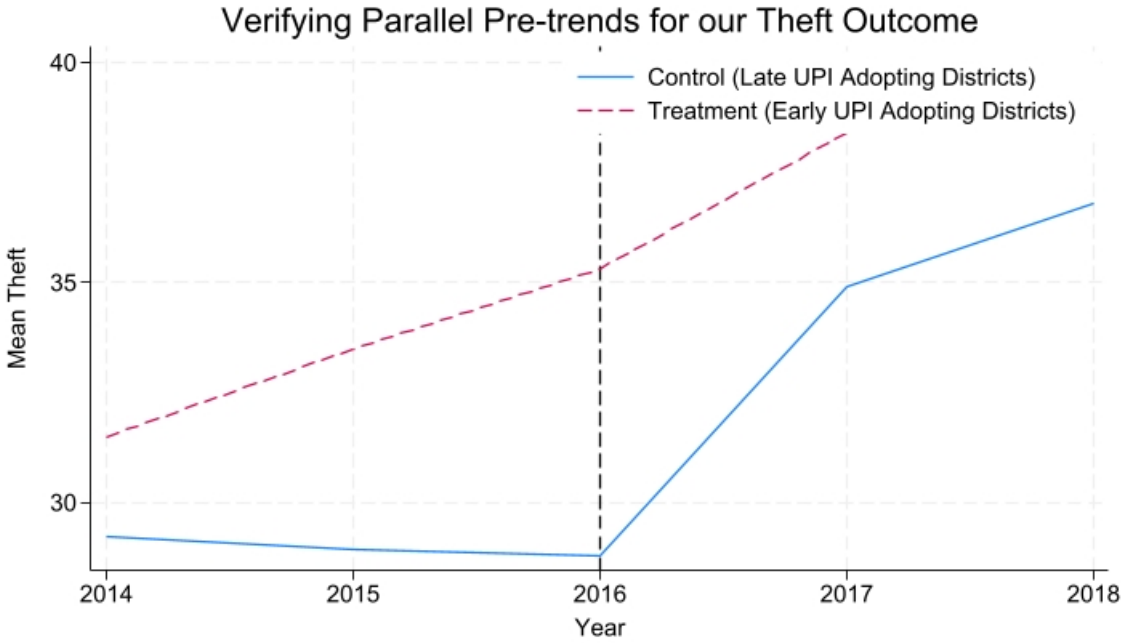
8 Appendix

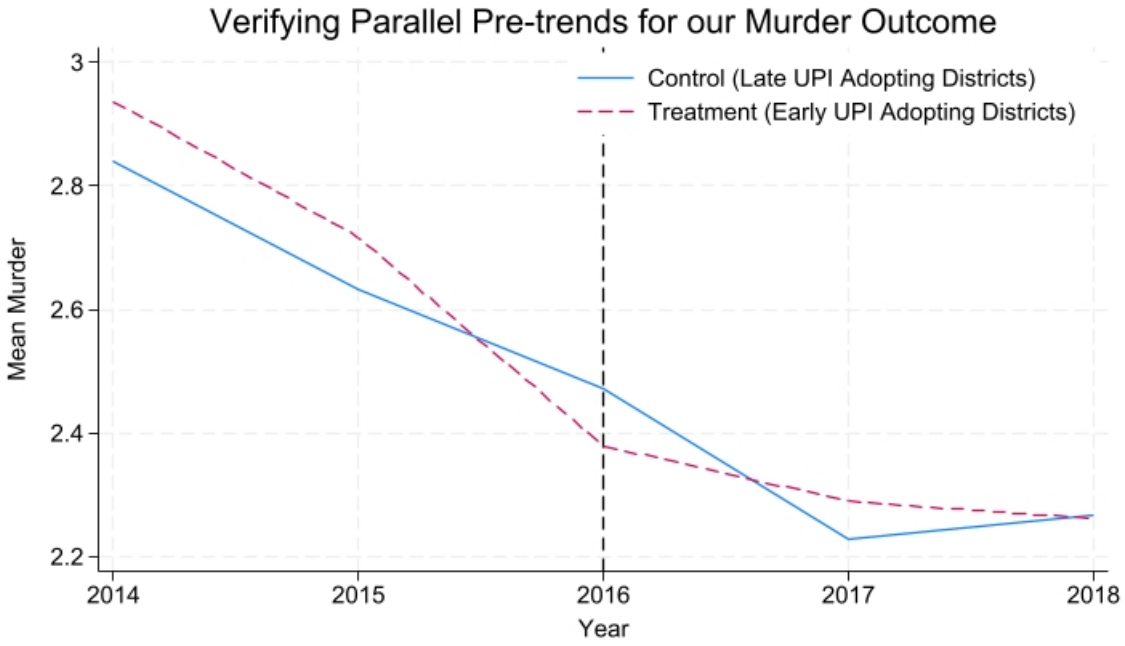
Table 6: Summary Statistics of Districts by Pre-Post Period

	Mean	SD	Min	Max	N
Pre-period					
Theft	32.28	84.91	0.00	1437.62	1886
Robbery	2.40	5.70	0.00	88.45	1886
Burglary	7.91	10.24	0.00	140.39	1886
Murder	2.67	1.78	0.00	34.08	1886
Post-period					
Theft	38.34	134.51	0.00	2090.03	1254
Robbery	1.89	3.45	0.00	70.09	1254
Burglary	5.11	7.97	0.00	96.59	1254
Murder	2.27	1.38	0.00	12.19	1254

Parallel Trends Graphs




Verifying Parallel Pre-trends for our Theft Outcome
Control (Late UPI Adopting Districts)
Treatment (Early UPI Adopting Districts)
Mean Theft
40
35
30
2014
2015
2016
2017
2018
Year


Verifying Parallel Pre-trends for our Murder Outcome
Control (Late UPI Adopting Districts)
Treatment (Early UPI Adopting Districts)
Mean Murder
3
2.8
2.6
2.4
2.2
2014
2015
2016
2017
2018
Year

Gendered Time Use: Do Community Food Programs Affect Women's Labour Force Decisions? [1]

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Ashoka University[2]

Abstract

Women in India face barriers to labor force participation due to entrenched gender norms, with rural women spending 301 minutes daily on unpaid domestic work compared to 98 minutes for men (TUS 2019). Cooking chores are a major constraint, limiting time for paid work. While subsidized food programs like Tamil Nadu's Amma Canteens primarily target food security, their impact on easing domestic burdens and boosting women's employment remains largely underexplored. Using TUS 2019 data, this study analyzes cooking time and employment outcomes across treated and control districts, employing different econometric methods. Findings show that subsidized food schemes reduce women's cooking time by 20–48 minutes daily, correlating with increased labor force participation. Additional factors like urbanisation, education, and access to clean cooking fuels also influence these patterns. This study highlights the role of welfare programs in addressing gendered domestic constraints, emphasizing their potential to enhance women's economic participation and broader economic development (Duflo, 2012).

[1]This paper was written under the guidance and supervision of Professor Ashwini Deshpande. We thank her for her inputs and suggestions throughout the process.

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1 Introduction

Gender norms in India have historically characterized women as the primary caregivers. Consequently, women spend a substantial amount of time daily on household activities. According to the Time Use Survey (TUS 2019), rural women spent 301 minutes per day on unpaid domestic services,[3] while rural men spent 98 minutes per day on the same tasks. This reflects the participation rate recorded for these tasks: 82.1% for rural women and 27.7% for rural men. Graph 1 highlights the difference in time spent on domestic tasks by men and women throughout the country.

An extensive range of scholarship has noted the correlation between this traditional division of work and women's decision-making (Badgett, 1999; Bridges et al., 2011; Ferrant et al., 2014). In particular, different employment surveys provide information on the chores performed by women and related economic benefits. Using NSSO data, Mehta and Pratap (2017) study the significance of women's principal activity status in their employment. They argue that tasks such as maintaining gardens and poultry, collecting firewood, and preserving meat are incorrectly categorized as not working. In this paper, we attempt to examine what opportunities arise when Indian women spend less time cooking.

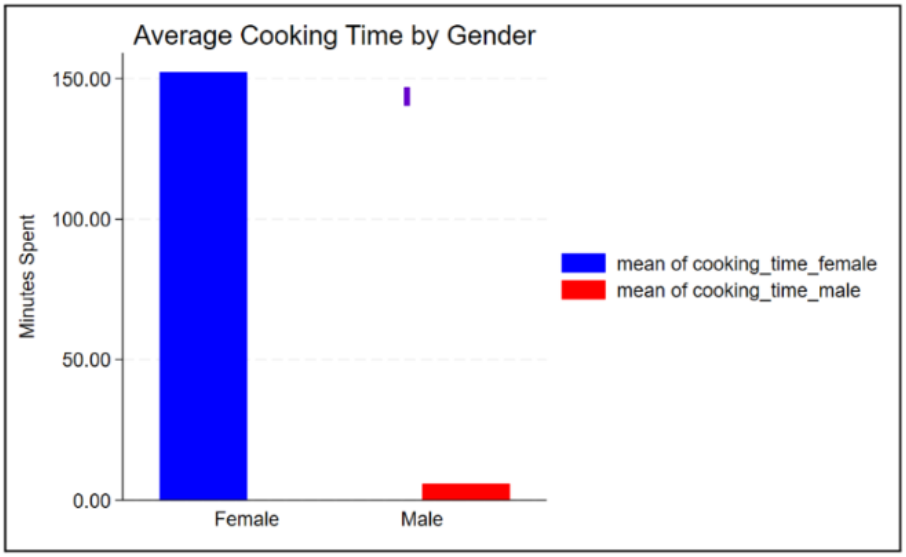


Figure 1: Average time in minutes spent on cooking by males and females across the country.

Subsidized food programs in India originally emerged to address food security and policy con-

[3]This included cooking, cleaning, pet care, etc.

cerns, particularly amongst the urban poor. These schemes aim to provide nutritious meals at extremely affordable prices. The concept gained attention, particularly after the launch of Amma Canteens[4] in Tamil Nadu in 2013. Their success had trickle-down effects, with each canteen employing 12 to 16 women (Mahendran and Indrakant, 2021). Soon, several states replicated this model – the Aahaar scheme was kickstarted in Odisha in 2015, Indira Canteens in Karnataka in 2017 and Annapurna Rasoi in Rajasthan in 2020.

By providing affordable meals, these schemes not only affect food insecurity but also the economic and time burden of household meal preparation. The time spent on these tasks by women, who primarily bear these responsibilities, can be redirected towards other opportunities. These could take the form of income-generating activities or acquiring skills to eventually earn. In this paper, we aim to study this relationship. We argue that subsidized food schemes reduce domestic time constraints for women, freeing up their time towards productive tasks. This will further contribute to women's labour force participation rates (LFPR). Using the TUS 2019 data, we examine the time spent on cooking and paid activities in regions with subsidized food schemes and those without.

2 Overview and Context

Trends in women's Labour Force Participation Rate (LFPR) in India have seen notable fluctuations over the years. The increases in LFPR have been attributed to the generation of self-employment and an increase in service sector jobs. On the other hand, decreases have been thought to be due to barriers to workforce entry. Gendered expectations of responsibilities limit women's time for paid work (Deshpande, 2021). Rising education levels have also led to delays or forgone entries into the labour force, particularly due to a skill mismatch (Andres et al., 2017). Insufficient childcare facilities and poor logistical factors (such as public transportation) are additional deterrents (Klasen and Pieters, 2015).

The challenge that domestic responsibilities pose to labour participation has been studied from the perspective of childcare in particular. Outsourcing this work removes hurdles to women's ability to engage in paid employment. Nandi et al. (2020) conduct a randomized trial in rural

[4]The scheme, started by then CM Jayalalitha, widely grew in prevalence and popularity

Rajasthan, assessing how access to affordable daycare helps women's economic outcomes two years later. They find that it increases the probability of women engaging in paid work by 2.6 percentage points. Another study that examines this phenomenon utilizes data from the Integrated Child Development Scheme (ICDS). It records an 8% increase in the probability of mothers finding employment, relative to the mean at baseline (Biswas and Adkins, 2024).

Other work has focused on the undervaluation of care work in India. Even paid care work, through Anganwadi centres and the Integrated Child Development Scheme, is underpaid and given limited recognition (Palriwala and Neetha, 2010). These tasks are characterized as being inherently "feminine." Overall shocks to the economy leave women even worse off: Deshpande (2021) records how the Covid-19 pandemic worsened the burden of domestic chores for women.

Wealth, marital status, caste and religion are all important factors to consider. A study of households in West Bengal finds that women being in charge of domestic chores lowers their probability of "working" (Deshpande and Kabeer, 2019). It documents that social markers such as religion do not significantly impact this figure. Other studies highlight the continued relevance of the caste gap in differential reactions to labour market shocks (Deshpande and Ramachandran, 2023). Intersectionality can play differing, region-specific roles in labour market outcomes.

Domestic burdens can also be reduced by technological advancements. Su and Azam (2023), using the TUS data, examine the impact of Liquified Petroleum Gas (LPG) on cooking time, and subsequently, their employment. They find that employment marginally increases as a result of LPG availability. This is in line with similar findings globally: as households in Sub-Saharan Africa used better more efficient types of fuel,[5] female labour participation rates saw improvement (Uchenna and Oluwabunmi, 2020). Their results show that earlier fuels had a high cost in terms of women's productive time.

In this study, we aim to highlight how gender norms pervade women's lives, affecting their choices, decisions and employment status. We specifically look at the time Indian women spend cooking and how food schemes lead to reductions in the same. This, as established,

[5] In comparison with solid fuel, which is less efficient

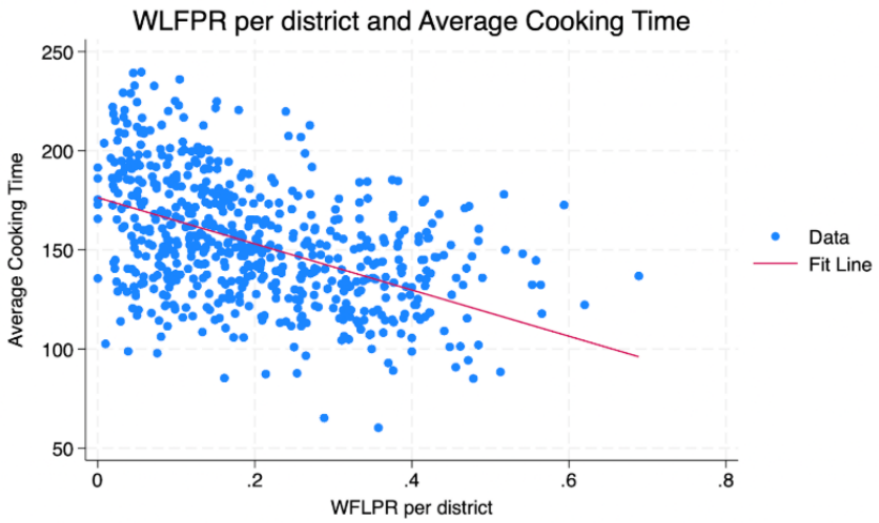


Figure 2: Preliminary estimation of average time spent on cooking by females vs WLFPR of each district.

can lead to increased labour participation. A preliminary visualization of the relationship between the time spent on cooking across states and WLFPR can be seen in Graph 2.[6] Increases in women's LFPR are crucial to India's overall growth picture, in terms of both economic and social welfare targets. The benefits of an increased workforce span different sectors – poverty reduction, gender equality and GDP growth. In developing countries, a 10% increase in women's participation in the labour market leads to a 3 to 5% increase in GDP per capita (Duflo, 2012). Despite this, Indian women contribute only 17% to the country's GDP in the status quo (World Bank, 2022). India's gender gap contributes significantly to the world average – when it is controlled for, the global number decreases by 10 percentage points (World Bank, 2022). The argument we put forth points to the importance of incorporating norms in policy and labour market decisions. The study itself is restricted to a select sample of regions. We look at certain districts that experienced a subsidized food scheme at the time of the TUS survey vis-a-vis those that did not experience such a scheme.

[6]The Women's Labor Force Participation Rate (WLFPR) for each district was estimated by calculating the average of the "paid employment status (women)" variable for each district.

3 Methodology

3.1 Data and Sample Collection

We examine the time spent by women on cooking using data from the Time Use Survey, 2019. The survey, conducted by the Ministry of Statistics and Programme Implementation, captures time use over a 24-hour period. The dataset records the time spent by men, women and other groups of people on paid and unpaid activities. It specifically has records of time spent on domestic tasks such as cooking, caregiving and cleaning. The dataset captures these patterns across 1,38,799 households and 4,47,250 individuals. This includes 2,73,195 individuals from rural areas and 1,74,055 from urban areas. For the purpose of the survey, each household in the sample was visited once.

Respondents were given a 24-hour recall period, and information was collected about activities they participated in from 4.00 AM the previous day to 4.00 AM on the day of the interview. This reference period was split into 48 time slots, of 30 minutes each. The survey was conducted over four sub-rounds that spanned a year. An equal number of subunits (divisions of regions based on populations) were surveyed in each subround. Hence, the data is cross-sectional, not longitudinal. This limits our analysis somewhat – it cannot have temporal elements. Most variables in the dataset are standard and were used in the original form. Activities in the data are categorised based on the International Classification of Activities for Time Use Statistics (ICATUS 2016), with 3-digit codes.

Table 1: List of treated, control districts and schemes for Models 1 and 2

Treated District	**State**	**Scheme**	**Control District**	**State**
Chandigarh	Chandigarh	Annapurna Akshaya Patra Yojana	Patiala	Punjab
			Sangrur (for placebo comparison)	Punjab
Annupur	Madhya Pradesh	Deen Dayal Yojana	Koriya	Chhattisgarh

As established earlier, subsidized food schemes are prevalent throughout the country. However, there are certain limitations to studying all of these schemes. First, some schemes, like the Indira Canteen in Karnataka, faced logistical hurdles and partially shut down (Goudar, 2024). Typically, these shutdowns are due to infrastructural failures or changes in the state government. Second, data on the spread and locations of food canteens under schemes is not readily

accessible for every state. For example, while the existence of the Antyodaya Anna Yojana in Jharkhand is known, records of where the scheme is located within the state are not accessible. Hence, for the purpose of this paper, we worked on an elimination basis. Starting with a list of states and their subsidized food schemes, we shortlisted on two counts. First, we checked for the active status of the scheme's operation in 2019, when the TUS data was collected. Second, we checked for records of districts within the state where the scheme was located. Based on the above, we constructed a sample that comprises three pairs of a treated district and a control district each.

Three models make up our empirical framework: the first is a baseline regression, the second has additional control variables to the same regression framework and the third is based on the method of Propensity Score Matching (PSM). Using three models helps ensure the robustness of our results.

In Models 1 and 2, districts are classified as treated if they experienced a subsidized food scheme conducted by their state government in the year 2019. On the other hand, they are classified as control if they did not experience a scheme at that point in time. The treated districts, the scheme they experienced, and the control district that they are weighed against are listed in Table 1. In the TUS data, we retain female data points from these select districts. The TUS questionnaire records time spent on "food and meals management and preparation." This is recorded within a variable called "cooking time" for all individuals and "cooking time female" for the retained data points. The stratifying of the dataset results in a sample of count observations.

To account for the labour force participation of the individuals in the sample, we set up a variable called "paid status." The labour force participation is determined by identifying individuals whose principal activity status, as recorded in the TUS questionnaire, falls under codes below 81. This classification includes all individuals engaged in self-employment, salaried employment, or casual employment, ensuring that all economically active individuals are accounted for in the labour force. The summary statistics of these variables and the other demographic factors involved are listed in Table 2. To account for the effect of various demographic factors on the relationship we are studying, we included covariates. Initially, these are limited to age,

education and marital status. While age and marital status are taken as given in the TUS data, education was a continuous variable. Hence, we condensed it into six categories.[7] We also use controls for "Urban Residency," "Monthly Consumption," "Social Group" and "Religion." Again, these variables were taken in their standard form as in the dataset. "Urban Residency" and "Monthly Consumption" were also aggregated to a district level average for further analysis.

Additionally, for the last section of our analysis, we use the NFHS dataset. This helps us in our PSM framework, explained further in the empirical framework. The NFHS survey offers district-level indicators on population, health, nutrition, etc. across the country. These help in matching comparable districts on the basis of different demographic factors. These are listed further in the framework. In Model 3 (PSM), we consider districts that have experienced a subsidized food scheme in the year 2019 to be treated and all other districts to be control.

3.2 Summary Statistics

Table 2 shows the mean and standard deviation of relevant variables and demographic factors. In treated districts, 36.6% of the sample resides in urban areas, while 39.4% of the control sample is urban. Additionally, 61.75% of the sample is classified as married, with the remainder as not married or widowed/divorced/separated.

As explained above, education is classified into six categories. 26.16% of women in the sample are illiterate, 54.02% have attained primary education and 9.92% have completed middle or secondary school. Meanwhile, 0.65% have completed higher secondary, 9.25% are graduates and above. 77.5% of the sample believed in Hinduism, 12.5% believed in Islam, 5.6% believed in Christianity. 1.83% believed in Sikhism, 0.26% in Jainism and 0.90% in Buddhism. Finally, 0.02% of the sample believed in Zoroastrianism and the rest classified as others. The monthly consumption in the treated areas averaged Rs. 6043, while in the untreated areas, it averaged Rs. 6683.

The average time spent on cooking in those districts where a food scheme was present is 145 minutes. On the other hand, in untreated districts, it is 154 minutes. While the difference here

[7] Illiterate, primary, middle and sec, higher sec, graduates and above.

seems minute, it is significant in comparing specific pairs (when other factors are more or less similar). 19.12% of the sample classified as employed (had a usual principal activity status < 81). Further, of those that are employed, 9.16% are engaged in self-employment, 4.88% in salaried labour, and 5.08% are engaged in casual labour. The NFHS indicators of the districts in the sample points to average employment being around 19%. Female literacy in these districts averages to 76%, while the measure of extent of sanitation among the population is 72%.

4 Effect of Cooking Time on Labour Participation

We set up an empirical framework to explore the relationship between subsidized food schemes and the differences in time spent on cooking by women. We compare treated districts to control or untreated districts, as defined above. We take on a three-fold approach: (1) a baseline regression focusing on border district comparisons, (2) enhanced regression models with additional control variables, and (3) propensity score matching (PSM) to address selection bias to ensure robust inferences.

4.1 Model 1: Baseline Regression

The first step in our empirical framework involves regressing the binary variable cooking time on the following dependent variables. This is a baseline regression to compare cooking time across districts with and without subsidized food schemes. The regression model is specified as follows:

$$\begin{aligned} CookingTime_{ij} = \beta_0 + \beta_1 PaidStatus_{ij} + \beta_2 Treated_{ij} + \beta_3 Age_{ij} \\ + \beta_4 Age_{ij}^2 + \beta_5 Education_{ij} + \beta_6 MaritalStatus_{ij} + \epsilon_{ij} \end{aligned} \tag{2}$$

Here, CookingTime$_{ij}$ represents the time spent on cooking by individual i in district j. PaidStatus$_{ij}$ is a binary variable indicating paid employment. Covariates include age (with its square), education, and marital status.

In this setup, we use the regression model to estimate cooking time for individuals in both treated and untreated districts. The key coefficient of interest is that on the Treated binary

variable. By comparing the coefficient for treated districts with that for untreated districts, we can directly assess the impact of the subsidized food scheme on cooking time.

4.2 Model 2: Enhanced Regression

To improve the precision of our estimates, we augment the baseline regression with additional covariates. These account for potential confounding factors. The enhanced regression is specified as:

$$\begin{aligned} \text{CookingTime}_{ij} = \beta_0 &+ \beta_1 \text{PaidStatus}_{ij} + \beta_2 \text{Treated}_{ij} \\ &+ \beta_3 \text{Age}_{ij} + \beta_4 \text{Age}_{ij}^2 + \beta_5 \text{Education}_{ij} \\ &+ \beta_6 \text{MaritalStatus}_{ij} + \beta_7 \text{Urban}_{ij} \\ &+ \beta_8 \text{SocialGroup}_{ij} + \beta_9 \text{MonthlyConsumption}_{ij} \\ &+ \beta_{10} \text{Religion}_{ij} + \epsilon_{ij} \end{aligned} \tag{3}$$

Here, the key additions to the model include urban residency, social group and religion, and monthly consumption expenditure. Urban residency accounts for differences in access to subsidized food schemes between urban and rural areas, which can significantly influence cooking patterns.

The social group and religion variables control for caste and religion-based disparities in time use and access to resources. Lastly, monthly consumption expenditure serves as a proxy for household economic status and helps differentiate the reliance on subsidized food schemes across income levels.

4.3 Model 3: Propensity Score Matching (PSM)

Finally, to address any selection bias – where districts with subsidized food schemes might systematically differ from untreated districts – we employ propensity score matching (PSM). This method ensures that treated districts are compared with untreated districts that have similar observable characteristics, thereby supporting the causal validity of our findings.

We estimate propensity scores using a logit model with the following covariates: average em-

ployment rate, urban proportion and monthly consumption expenditure, female literacy rate, percentage of households with clean cooking fuel, sanitation access and sex ratio, and percentage of women married below 18. The first covariate reflects economic activity levels that may correlate with scheme implementation and the second captures urbanization's influence on access to subsidized food schemes. The female literacy rate reflects the proportion of educated women, which may influence time use patterns. The cooking fuel variable represents the accessibility of resources that may reduce cooking time. The last few variables also represent broader social development indicators and socio-cultural norms that are relevant to our study.

We employ nearest-neighbor matching with a caliper of 0.1, ensuring that treated and untreated districts are closely matched in terms of their propensity scores. Post-matching, we compare the average cooking time between treated and untreated groups to estimate the average treatment effect.

In using this three-model framework, we attempt to achieve consistency in our results across different specifications. This approach ensures that our findings are not sensitive to the choice of model, providing more robust estimates of the effect of subsidized food schemes on cooking time and consequently, on labour participation.

5 Findings

Tables 3, 4 and 5 show the results of the three estimations. We discuss the model-wise results below.

5.1 Model 1

Using Model 1, we first perform a pairwise comparison between Chandigarh (treated district) and Patiala (control district). We see that the coefficient on the treated variable is statistically significant, suggesting that women in the treated district (Chandigarh) spend, on average, 20 minutes less on cooking compared to women in Patiala. This suggests that the implementation of the food scheme in Chandigarh has reduced the time spent on cooking activities by women. Next, we compare Anuppur (treated district) and Koriya (control district). The coefficient on

the treated variable is again significant. It shows that women in Anuppur spend 30 minutes less on cooking than those in Koriya.

We also use Sangrur and Patiala as placebo districts to test whether the observed difference in cooking time between treated and non-treated districts is due to the scheme itself. Both districts, being non-treated, should not show a significant difference (if the scheme is the true cause of variation in cooking time). The coefficient on the treated variable in the placebo analysis is insignificant, indicating that there is no significant difference in cooking time between Sangrur and Patiala. This suggests that the observed variation in cooking time between treated and non-treated districts in the main analysis is likely the scheme itself, rather than other factors.

5.2 Model 2

In Model 2, we include additional controls such as social group, religion, monthly expenditure, and urbanicity, while testing the same pairwise comparisons as in Model 1. Our results remain largely consistent, with only minor adjustments, confirming the robustness of the initial findings.

For the comparison between Patiala and Chandigarh, the difference in time spent cooking by women in Chandigarh (treated) compared to Patiala (control) increases by 1 minute. In the placebo comparison between Patiala and Sangrur, the difference in cooking time remains insignificant. This indicates that the food scheme's effect is not being incorrectly attributed to non-treated districts, supporting the validity of the treatment effect.

When comparing Anuppur (treated) and Koriya (control), the time difference in cooking between the two districts is now approximately 27 minutes, which is a slight decrease from the 30 minutes observed in Model 1. Despite this adjustment, the result still shows a significant difference. Furthermore, the R^2 for all pairwise comparisons in this model increases, indicating that the additional controls help explain more of the variation in cooking time. This improvement in model fit suggests that the added factors – such as social group, religion, and urbanicity – are relevant in explaining the differences in cooking time across districts.

5.3 Model 3

Model 3, which uses Propensity Score Matching, provides further evidence. In the unmatched comparison, women in the treated districts (e.g., Chandigarh, Anuppur) spend, on average, 8.35 minutes less on cooking compared to those in control districts (e.g., Patiala, Koriya). This is statistically significant. This suggests that the implementation of food schemes in treated districts is associated with a reduction in cooking time.

After applying propensity score matching (PSM) to control for observable socioeconomic characteristics, the average treatment effect on the treated (ATT) reveals a substantial reduction in cooking time: women in treated districts spend 48.97 minutes less on cooking compared to those in control districts. This reduction is larger than the differences observed in Model 1 (30 minutes) and Model 2 (27 minutes), highlighting the improved balance achieved through matching in Model 3.

The logistic regression coefficients used in the propensity score estimation indicate how various factors influence the likelihood of being in a treated district. Specifically, higher employment rates, a greater proportion of urban households, and higher average monthly consumption expenditure are associated with a higher probability of treatment (i.e., being in a district with the intervention). In contrast, higher female literacy rates, a greater proportion of marriages under 18, and better access to clean fuel and sanitation are associated with a lower probability of treatment.

Some of these relationships may seem counterintuitive at first glance. For instance, one might expect higher employment rates and urbanization to correlate with better socioeconomic conditions, making treatment less likely. However, this pattern could reflect targeting strategies where programs are implemented in areas with a mix of both need and administrative feasibility.

In conclusion, our results consistently support the hypothesis that food schemes significantly reduce the time women spend cooking in treated districts. Across all three models – Model 1 (pairwise comparison), Model 2 (with additional controls), and Model 3 (Propensity Score Matching) – we observe a clear and statistically significant reduction in cooking time for women in treated districts.

6 Discussion and Concluding Remarks

Subsidized food schemes have been lauded for their success in reducing food insecurity and poverty. These reasons have alone prompted their expansion throughout the country. Our analysis points to another clear benefit that arises from these schemes. By helping women somewhat escape their domestic burden, these schemes have the potential to significantly help labour force participation. As other work has made clear, they also help in directly employing women, by providing them with a paid avenue to perform what is considered domestic work.

A limitation of our analysis, however, is its cross-sectional design. Without access to time-varying data on cooking time, we rely on a single comparison between districts with and without subsidized food schemes. This restricts our ability to establish causality over time. Any observed differences in cooking time could be influenced by other unaccounted temporal factors, such as broader economic fluctuations or policy changes. These might be affecting cooking time independently, outside of the subsidy scheme. It is also challenging to isolate the long-term impacts of the food schemes from the short-term: to examine whether there are prolonged impacts from experiencing a scheme for longer. Additionally, lesser districts qualified for our analysis – they are relevant only if they experienced a scheme in 2019, at the time of the TUS survey.

The TUS data captures self-reported estimates of time spent on different activities, including cooking. This may not fully capture the intricacies of time use at the individual level, leading to potential measurement bias. Finally, our analysis assumes that the relationship between subsidized food schemes and cooking time is uniform across all districts, not accounting for potential heterogeneity in how different regions respond to these policies. Factors such as local cultural norms, access to alternative food sources, or varying levels of government enforcement could lead to differential impacts across districts, which our model does not fully address.

Our sampling has its disadvantages too. The small n-size limits the external validity of the results, making them less generalizable. The diversity of the country – broadly different bureaucracy, government types and infrastructure – means the results derived based on two states (Chandigarh and Madhya Pradesh) cannot be extended to all those that have experienced food schemes. However, our analysis lays the groundwork for future research on the subject. If data

on more schemes and their implementation can be mined, the analysis can be extended to more states. Rural women likely face bigger hurdles in terms of the domestic responsibilities. Urban households often distribute the burden by employing domestic helpers (Deshpande, 2020). There is scope to examine micro-differences in rural and urban areas that have experienced a food scheme. While our two pairs are distinct in this sense – Chandigarh and Patiala are urban districts compared to Anuppur and Koriya – they do not provide enough basis to derive rural-urban inferences.

Women are, as a demographic, disproportionately harmed by shocks. Their contribution to the labour force, as noted earlier, has marked positive effects on the economy. Given this, the results of our paper are hopeful. They suggest that the empowerment of women can come through schemes that have multifold welfare benefits. As Duflo (2012) notes, pushing the lever of women's empowerment is a virtuous cycle, and sets off a series of developmental benefits. Ferrant (2014) posits what the analysis of this paper has reinforced: time use patterns reflect the attribution of gender roles. These govern activities and labour divisions, separated as "feminine" and "masculine." The argument this paper puts forth could represent a broader shift in undoing such norms through the reduction of cooking time. By providing a mechanism that eases this burden directly, food schemes may, in the long-term, weaken gender norms and women's overall economic participation.

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7 Tables

Table 2: Summary Statistics

Variable	**Treated (n=12,624)**	**Control (n=189,661)**
	Mean (Std. Dev.)	*Mean (Std. Dev.)*
Cooking Time (min)	145.25 (121.67)	153.60 (124.50)
Paid Status	1.01 (0.25)	1.02 (0.36)
Urban	0.37 (0.48)	0.39 (0.49)
Religion	1.11 (0.46)	1.46 (1.15)
Social Group (n)	2.62 (1.00)	2.86 (0.99)
Monthly Cons. Exp.	6,042.61 (4,005.84)	6,683.07 (4,022.36)
Age	33.57 (17.93)	34.92 (17.77)
Marital Status	1.79 (0.60)	1.84 (0.61)
Education (Index)	0.96 (1.00)	1.14 (1.10)
NFHS Variables	**Obs**	**Mean (Std. Dev.)**
Avg. Employment Rate	202,380	0.20 (0.12)
Urban Proportion	202,380	0.39 (0.25)
Avg. Monthly Cons. Exp.	202,285	6,643.10 (1,512.60)
Female Literacy (%)	202,246	76.08 (11.93)
Household Clean Fuel (%)	202,246	58.13 (23.30)
Population Sanitation (%)	202,246	72.18 (14.05)
Sex Ratio (per 1000)	202,246	1,020.65 (71.63)

Notes: Summary statistics are provided for treated and control groups in the first section. NFHS-specific variables are reported in the second section with corresponding standard deviations and ranges.

Table 3: Impact of Food Scheme on Cooking Time

	Chandigarh vs Patiala	**Sangrur vs Patiala**	**Annuppur vs Koriya**
	Coefficient (SE)	Coefficient (SE)	Coefficient (SE)
Treated District	-20.68^{***}	3.50	-30.96^{**}
	(6.89)	(6.22)	(10.89)
Paid Employment (binary)	-58.19	-39.11	42.42
	(64.13)	(34.99)	(102.26)
Age	7.45^{***}	8.09^{***}	7.12^{***}
	(1.16)	(1.03)	(1.63)
Age Squared	-0.10^{***}	-0.11^{***}	-0.09^{***}
	(0.01)	(0.01)	(0.02)
Marital Status (Reference: Never Married)			
Married	145.49^{***}	153.43^{***}	135.05^{***}
	(12.60)	(12.07)	(20.08)
Divorced	89.82^{***}	73.75^{***}	108.44^{***}
	(18.75)	(17.19)	(28.47)
Widowed	68.90	–	189.90^{**}
	(65.15)	–	(75.40)
Education			
Primary	4.20	18.52^{**}	19.69
	(9.62)	(9.02)	(13.86)
Middle & Secondary	23.83*	28.30^{**}	71.16^{***}
	(12.80)	(12.15)	(22.36)
Higher Secondary	-68.58	-9.04	-93.69
	(45.95)	(53.65)	(103.94)
Graduates & Above	-15.72	24.18^{**}	60.39^{*}
	(11.70)	(11.90)	(33.81)
Constant	-40.48^{**}	-75.83^{***}	-40.64
	(19.07)	(17.54)	(27.99)
Observations	747	882	383
R-squared	0.4692	0.5159	0.4137
Adj. R-squared	0.4613	0.5103	0.3964

Notes: Robust standard errors are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Columns represent results for Chandigarh vs Patiala, Sangrur vs Patiala, and Annuppur vs Koriya, respectively. – indicates no data.

Table 4: Impact of Additional Covariates on Cooking Time

	Patiala & Chandigarh	**Patiala & Sangrur**	**Annupur & Koriya**
	Coefficient (SE)	Coefficient (SE)	Coefficient (SE)
Treated (Reference: Untreated)			
Chandigarh	−21.97**		
	(8.54)		
Sangrur		9.24	
		(6.35)	
Annupur			−27.30**
			(12.33)
Age	7.27***	7.97***	6.86***
	(1.17)	(1.03)	(1.62)
Age Squared	−0.10***	−0.10***	−0.09***
	(0.01)	(0.01)	(0.02)
Education			
Primary	7.53	18.85**	14.29
	(9.77)	(9.13)	(13.93)
Middle & Secondary	29.53**	27.94**	61.11***
	(13.17)	(12.44)	(22.64)
Higher Secondary	−72.52	−21.27	−59.48
	(46.20)	(53.55)	(102.43)
Graduates & Above	−6.35	25.39**	38.43
	(12.43)	(12.50)	(35.86)
Marital Status (Reference: Never Married)			
Married	143.93***	153.46***	143.27***
	(12.64)	(12.00)	(20.13)
Divorced	87.54***	74.39***	118.75***
	(18.83)	(17.09)	(28.36)
Widowed	73.22	–	191.47**
	(65.09)	–	(74.79)
Urban	−19.40**	−8.76	2.42
	(8.91)	(8.15)	(13.41)
Social Group (Reference: ST)			
SC	−15.83	−94.91	40.28**
	(41.09)	(64.79)	(15.54)
OBC	−10.56	−99.21	24.03*
	(41.66)	(64.94)	(13.58)
Others	−13.00	−100.06	5.47
	(40.93)	(64.82)	(21.60)
Religion (Reference: Hinduism)			
Islam	17.43	−56.63***	44.58
	(20.54)	(19.17)	(33.04)
Christianity	−25.64	−37.75	6.77
	(52.45)	(64.87)	(33.52)
Sikhism	−22.76***	−23.62***	–
	(8.44)	(7.66)	–
Jainism	−74.56	−86.98	34.20
	(52.91)	(53.21)	(44.55)
Monthly Cons. Exp.	−0.0003	0.0008	0.0036**
	(0.0010)	(0.0009)	(0.0014)
Constant	−8.76	31.75	−76.13***
	(46.79)	(67.95)	(28.98)
Observations	747	882	383
R-squared	0.480	0.531	0.447
Adj. R-squared	0.465	0.520	0.418

Notes: Standard errors are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Logistic Regression Results and ATT Estimates

Logistic Regression Results			
Variable	**Coefficient**	**Std. Err.**	**z**
Cooking Time	-0.0005505^{***}	(0.0000886)	-6.21
Avg. Employment Rate	6.960536^{***}	(0.0975205)	71.38
Middle Male %	0.0041275^{***}	(0.0002354)	17.53
Urban Proportion	3.852368^{***}	(0.0698606)	55.14
Avg. Monthly Cons. Exp.	-0.0003078^{***}	(0.0000081)	-37.80
Women Married Below 18	-0.0554968^{***}	(0.0012964)	-42.81
Female Literacy %	-0.0667095^{***}	(0.0015087)	-44.22
Households with Clean Fuel %	-0.0649049^{***}	(0.0008372)	-77.53
Sanitation Access %	-0.0365542^{***}	(0.0011776)	-31.04
Sex Ratio	-0.0235014^{***}	(0.0002418)	-97.21
Constant	31.36959^{***}	(0.3040781)	103.16

ATT Estimates					
Variable	**Sample**	**Treated**	**Controls**	**Difference (S.E.)**	
Cooking Time	Unmatched	145.246	153.595	-8.349 (1.143)	$t = -7.30$
	ATT	145.246	194.218	-48.972 (9.241)	$t = -5.30$

Notes: Standard errors are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. ATT results indicate the Average Treatment Effect on the Treated. Standard errors do not account for the estimation of the propensity score.

Towards a Richer and More Accessible Understanding of Inequality

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1 Problem Statement

How can the Atkinson Index be adapted to improve its sensitivity and applicability in diverse economic contexts?

We derive a simplified measure, $\sigma_A(x)$ with the value judgements of the Atkinson Index baked into it, representing the share of the poorer individual in a two-person equivalent economy. We apply econometric methods on the WPID dataset to validate this index as an inequality measure. We also make the case for increasing the use of the Atkinson Index alongside the ubiquitous Gini coefficient by demonstrating how increasing inequality aversion significantly alters the narrative around inequality. We aim to provide policymakers and economists an accessible tool to measure inequality tailored to their own value judgments.

2 Motivation

2.1 Narrative Around Inequality

We believe that the convention around inequality is faced by two major problems. Inequality measurement currently revolves around the Gini coefficient. Although the Gini coefficient is a good representation of the income distribution, it does not disclose the implicit value judgements or social welfare considerations made in its calculation[2]. However, inequality and social welfare are intricately linked – making this a critical flaw. This makes an ethical notion of inequality aversion desirable because measuring it inherently involves value judgments about fairness, the priorities of society and the trade-offs between equity and efficiency. As for the

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[2]Creedy, J. *Comparing Income Distributions Using Atkinson's Measure of Inequality.* 2021.

second problem, it deals with the fact that inequality measurement at large is increasingly esoteric. Though measures like the Gini coefficient, the Atkinson Index, the Theil Index, etc. carry a lot of useful information in their own rights, there is a lack of an intuitive, relatively elementary measure of inequality that is simple to understand for the layman.

2.2 Atkinson Index

The Atkinson Index is a measure of income inequality developed by British economist Anthony Barnes Atkinson[3]. It can be turned into a normative measure by imposing a parameter ϵ to weight incomes (higher ϵ makes $A(x)$ more sensitive to incomes at the lower end of the distribution), known as the level of inequality aversion, making it a strong candidate to solve the first problem of inequality measurement. The Atkinson Index w.r.t ϵ is defined as follows:

$$A(x) = 1 - \frac{x_e}{\mu(x)}$$

$$x_e = \begin{cases} \left(\frac{1}{n}\sum_{i=1}^{n} x_i^{1-\epsilon}\right)^{\frac{1}{1-\epsilon}} & 0 \leq \epsilon \neq 1 \\ \left(\prod_{i=1}^{n} x_i\right)^{\frac{1}{n}} & \epsilon = 1 \\ \min(x_1, x_2 \dots x_n) & \epsilon = +\infty \end{cases}$$

Here, x_e is the equally distributed equivalent income. Hence, the Atkinson Index $A(x) \in [0, 1]$ for some ϵ represents the share of total income that would have to be sacrificed to instate perfect equality without reducing overall welfare.

The Atkinson Index satisfies most of the axioms desired for an inequality measure. Additionally, it possesses several unique properties, e.g. subgroup decomposability – the class of subgroup decomposable indices is very restrictive, and doesn't include the Gini coefficient.

[3] Atkinson, A.B. *On the measurement of inequality*. Journal of Economic Theory, 2 (3), pp. 244–263, 1970.

This makes it a compelling research prospect.

3 Analytical Framework: Mathematical Exposition

3.1 Model

We use an isoelastic underlying utility function of the following form for our model. A utility function of this kind is a widely popular choice because it is additive and individualistic and also allows us to maintain the valuable properties of the Atkinson Index, such as subgroup decomposability and consideration for relative as opposed to absolute income differences.

$$U(x) = \begin{cases} \frac{x^{1-\epsilon}}{1-\epsilon} & \epsilon \neq 1 \\ \\ \ln(x) & \epsilon = 1 \end{cases}$$

3.2 Mathematical Approach

We use the aforementioned utility function and leverage its additive property to develop the notion of a Normalised Atkinson Index $\tilde{A}(x)$ for a vector of incomes in increasing order $x = (x_1 \dots x_n)$. The Normalised Atkinson Index is useful because it ensures comparability across different distributions by always yielding the maximum value of 1, regardless of the size of the distribution.

Then, taking inspiration from Subramaniam (1995)[4], we construct an equivalent two-person economy with the income vector $x^* = (x_1^*, x_2^*)$ such that $\mu(x) = \mu(x^*)$ and $\tilde{A}(x) = \tilde{A}(x^*)$. This helps us derive an index σ_A representing the share of cake that the poorer person gets in a two-person cake-sharing problem.

[4]Subramaniam, S. *Towards a simple interpretation of the Atkinson class of inequality indices*, 1995.

3.3 Approach to Data

3.3.1 Calculating Indices

We use a longitudinal panel dataset containing the mean incomes of decile groups in different countries across time to calculate the Gini coefficients and Atkinson indices for different values of ϵ.

We could treat these deciles as a sample of 10 representative people and use their incomes to calculate our inequality indices. However, due to the jagged nature of the Lorenz Curves generated by these incomes, we feel that the indices calculated using this method may be downward estimates[5].

Hence, we extrapolate Peter Ellis' method for calculating Gini Coefficients from mean incomes of decile groups and use it to calculate Atkinson Indices for different values of $\epsilon(= 0.25, 0.5...1.75, 2)$:

1. Assume that our 10 decile mean incomes represent the quantiles (0.05, 0.1 . . . 0.9, 0.95).

2. Pick a log-normal distribution that fits these binned incomes best. Income is often modelled as a log-normal distribution since it produces non-negative, compounded values as opposed to additive values, which fits the nature of income better.

3. Generate individual-level data using this log-normal distribution and find the binned decile means using this data. Then, generate the inequality index using this sample of 10 observations.

Then, we calculate the Normalised Atkinson Index $\tilde{A}(x)$ and utilise root-solving methods to solve for $\sigma_A(x)$ for $\epsilon = (0.25, 0.5, 0.75)$.

3.3.2 Sanity Checks

We plot the Kuznets Curves (Inequality Index Value vs Log of GDP per Capita (2005 PPP)) using relatively conventional indices including the Gini coefficient and the Atkinson Index for $\epsilon = (0.25, 0.5, 1, 2)$. Then, we plot the Kuznets Curves for $(1 - \sigma_{0.25}(x))$ and $(1 - \sigma_{0.5}(x))$ to

[5]Ellis, P. "Estimating Gini coefficient when we only have mean income by decile." *Free Range Statistics*, 2017.

ensure expected behaviour. Note that we take $(1 - \sigma_\epsilon)$ as it represents the share of the richer in the two-person economy, i.e. the perceived inequality.

Then, we hoped (and failed) to replicate Deininger and Squire (1998)'s exercise of making the Kuznets relationship vanish by adding region (specifically, a dummy variable for Latin America) specific controls. First, we use the original Kuznets regression specification and find a significant relationship between log of GDP per capita and inequality, increasing and then decreasing.

$$I(x) = \beta_0 + \beta_1 X_i + \beta_2 \left(\frac{1}{X_i}\right) + e_i$$

Where X_i is GDP per Capita (2005 PPP). Then, we account for region-fixed effects and time-fixed effects using the following regression specification.

$$I(x) = \beta_0 + \beta_1 X_i + \beta_2 \left(\frac{1}{X_i}\right) + \text{i.region} + (\text{i.year})$$

Where $i.region$ represents controlling for region-fixed effects and $i.year$ represents controlling for year-fixed effects. Unfortunately, due to the limitations of our dataset, we again receive a false confirmation of the Kuznets hypothesis.

$\sigma_A(x)$ is a non-linear function of $A(x)$ for a given ϵ. To verify our mathematical exposition, we demonstrate a diagrammatic representation of the $\sigma_A(x)$ index over years for $\epsilon = (0.25, 0.5, 0.75)$ for India.

3.3.3 Limitations of the Gini Coefficient

After observing a large difference in means between the Gini coefficient and the Atkinson Index at $\epsilon = 2$, we explore how this difference varies for countries based on their income group. We adjust the World Bank income groups from 2023[6] for inflation to get reasonable proxies of these income groups for 2005. After splitting our dataset according to these income groups, we analyse the difference in means between Gini and $A(x)$ at $\epsilon = 2$ using a ttest.

[6] *World Bank Income Groups.* Our World in Data, 2024.

4 Data Sources

We use the LM-World Panel Income Distribution dataset[7], containing mean incomes (2005 PPP) of decile groups in 158 countries (and data split it into Urban and Rural areas for China, India, and Indonesia) from 1986-2010 from 565 household-level surveys, merging data from PovcalNet, World Income Distribution (WYD), Luxembourg Income Study (LIS), the British Household Panel Survey (BHPS), the European Union Survey of Income and Living Conditions (SILC), and data from country statistical offices.

5 Findings

5.1 Mathematical Exposition

We derive x_e, the equally distributed equivalent income, which satisfies the following condition:

$$W(x_e \dots x_e) = W(x_1 \dots x_n)$$

We solve this equation using the additive property of our utility function.

$$n \cdot \frac{x_e^{1-\epsilon}}{1-\epsilon} = \sum_{i=1}^{n} \frac{x_i^{1-\epsilon}}{1-\epsilon}$$

$$x_e = \left(\frac{1}{n} \cdot \sum_{i=1}^{n} x_i^{1-\epsilon} \right)^{\frac{1}{1-\epsilon}} \tag{4}$$

Now, we find x_m, the equally distributed income with overall utility equivalent to a perfectly unequal income distribution, i.e. where one person appropriates the entire income. It must satisfy the condition:

$$W(x_m \dots x_m) = W(n\mu(x) \dots 0)$$

[7]Lakner, C. & Milanovic, B. *Global Income Distribution: From the Fall of the Berlin Wall to the Great Recession*. The World Bank Economic Review, vol. 30, Issue 2, pp. 203–232, 2016.

Table 1: Descriptive Statistics grouping by Year: Mean Income/Decile, GDP-PC (2005 PPP)

Year	Variable	Mean	Min	Max	SD
1986	RRmean	6392.89	559	16411	5205.41
1986	GDP-PC	12905.9	837.083	29269.2	9923.9
1987	RRmean	4406	417	14401	4522.42
1987	GDP-PC	10773.1	958.37	26127.9	8918.75
1988	RRmean	4143	402	12709	3269.84
1988	GDP-PC	9130	723.007	24021.9	6694.61
1989	RRmean	4988.64	441	13913	4107.62
1989	GDP-PC	10765.4	547.359	24801.8	7949.99
1990	RRmean	2618.3	407	7030	2193.54
1990	GDP-PC	7613.85	2029.22	19776.7	6688.37
1991	RRmean	8495.09	584	16370	5698.36
1991	GDP-PC	16353	674.739	31392.9	10891.2
1992	RRmean	2718.19	245	12325	2803.79
1992	GDP-PC	6257.22	574.129	26127.5	6417.55
1993	RRmean	2594.72	230	14596	3003.95
1993	GDP-PC	6765.61	807.606	29482.7	6778.98
1994	RRmean	5315.29	287	18156	5984.43
1994	GDP-PC	12094.9	592.611	48410.7	12660.4
1995	RRmean	4608.89	503	13778	4838.02
1995	GDP-PC	10255	485.483	37810.6	10987.4
1996	RRmean	3087.36	360	14330	4114.98
1996	GDP-PC	6220.86	415.957	20147.5	7109.38
1997	RRmean	3598.21	354	18471	4551.66
1997	GDP-PC	8824.49	667.68	35881	10159.9
1998	RRmean	4544.57	292	19902	4834.24
1998	GDP-PC	10302.3	517.959	53353.7	11303
1999	RRmean	3037.52	316	12362	3504.22
1999	GDP-PC	8727.42	510.418	30991.6	8958.51
2000	RRmean	7335.65	464	17833	6324.26
2000	GDP-PC	16688.3	660.952	43974.8	13926.4
2001	RRmean	1990.73	319	8858	2407.58
2001	GDP-PC	4049.8	825.5	22621.5	6031.21
2002	RRmean	2302.76	439	15621	3218.52
2002	GDP-PC	5906.32	577.92	28944.6	7460.17
2003	RRmean	2786.78	486	12602	2854.26
2003	GDP-PC	6988.31	611.728	40134.4	7752.16
2004	RRmean	7014.17	409	23329	7283.69
2004	GDP-PC	17774.4	646.122	65800.2	17292.4
2005	RRmean	5752.97	261	16544	5822.67
2005	GDP-PC	13864.7	276.993	38896.4	12943.6
2006	RRmean	1720.11	348	5590	1580.63
2006	GDP-PC	4946.11	496.781	19282.5	5912.07
2007	RRmean	1434.31	326	5695	1361.47
2007	GDP-PC	3016.56	401.907	11238.4	2811.88
2008	RRmean	7054.92	179	24273	6412.16
2008	GDP-PC	17983.2	303.193	73349.6	14665
2009	RRmean	1900.27	479	5924	1634.95
2009	GDP-PC	5088.71	54084.89	13832.5	4591.62
2010	RRmean	598.2	336	817	154.807
2010	GDP-PC	1054.55	795.492	1488.29	243.487

Table 2: Descriptive Statistics grouping by Region: Mean Income/Decile, GDP-PC (2005 PPP)

Region	Variable	Mean	Min	Max	SD
China	RRmean	990	407	2372	575.408
China	GDP-PC	2579.48	958.37	5238.68	1498.08
India	RRmean	633.933	514	876	96.3909
India	GDP-PC	1692.64	1052	2573.14	557.587
L. America & Carib.	RRmean	3031.88	666	14330 & 1597.67	
L. America & Carib.	GDP-PC	6752.07	1106.42	15826.3	3117.43
M. East & N. Africa	RRmean	1842.52	778	3676	657.315
M. East & N. Africa	GDP-PC	4409.55	1758.41	9228.24	1749.93
Mature economies	RRmean	10628.9	1190	24273	5065.5
Mature economies	GDP-PC	24580.6	5920.8	73349.6	10922.2
Other Asia	RRmean	1130.64	417	4797	821.508
Other Asia	GDP-PC	3045.41	723.007	12526.3	2448.29
Russia, C. Asia, SE Europe	RRmean	2519.28	230	9201	1750.69
Russia, C. Asia, SE Europe	GDP-PC	5843.36	904.566	17300.3	3751.94
Sub-Saharan Africa	RRmean	847.739	179	5622	808.805
Sub-Saharan Africa	GDP-PC	2018.07	276.993	19282.5	3019.91

Table 3: Descriptive Statistics grouping by Decile: Mean Income in Decile (2005 PPP)

Decile	Variable	Mean	Min	Max	SD
1	RRinc	1218.5	21	9482	1641.09
2	RRinc	1946.87	39	13368	2548.98
3	RRinc	2423.96	60	15750	3092.79
4	RRinc	2860.57	86	17722	3576.21
5	RRinc	3317.57	110	19567	4077.98
6	RRinc	3837.72	134	21624	4645.72
7	RRinc	4468.52	164	24385	5327.7
8	RRinc	5325.51	210	29048	6248.49
9	RRinc	6707.22	289	38077	7646.1
10	RRinc	12223.3	577	72925	12734.1

Again, we use the additive property of our utility function to solve for x_m.

$$n \cdot \frac{x_m^{1-\epsilon}}{1-\epsilon} = \frac{(n\mu(x))^{1-\epsilon}}{1-\epsilon}$$

$$x_m = \mu(x) \cdot n^{\frac{-\epsilon}{1-\epsilon}} \tag{5}$$

Now, so that inequality is reasonably comparable between our given distribution and a two-person economy, and is always = 0 for minimum inequality and = 1 for maximum inequality, we define the Normalised Atkinson Index for an income distribution and a given ϵ as follows:

$$\tilde{A}(x) = \frac{\mu(x) - x_e}{\mu(x) - x_m} \tag{6}$$

Then, we construct an equivalent two-person economy such that the following conditions hold:

$$x_1^* + x_2^* = 2\mu(x) \quad \text{and} \quad \tilde{A}(x^*) = \tilde{A}(x)$$

Using our definition of the normalised Atkinson Index, we derive:

$$\tilde{A}(x) = \tilde{A}(x^*) = \frac{\mu(x) - \left(\frac{1}{2} \cdot \{x_1^{*1-\epsilon} + x_2^{*1-\epsilon}\}\right)^{\frac{1}{1-\epsilon}}}{\mu(x) \cdot \left(1 - 2^{\frac{-\epsilon}{1-\epsilon}}\right)} \tag{7}$$

We simplify this equation as follows:

$$x_1^{*1-\epsilon} + x_2^{*1-\epsilon} = 2\left(\mu(x) \cdot \{1 - \tilde{A}(x) \cdot (1 - 2^{\frac{-\epsilon}{1-\epsilon}})\}\right)^{1-\epsilon} \tag{8}$$

Now, we rewrite this equation in terms of x_1^* using the relationship $x_1^* + x_2^* = 2\mu(x)$.

$$x_1^{*1-\epsilon} + (2\mu(x) - x_1^*)^{*1-\epsilon} = 2\left(\mu(x) \cdot \{1 - \tilde{A}(x) \cdot (1 - 2^{\frac{-\epsilon}{1-\epsilon}})\}\right)^{1-\epsilon} \tag{9}$$

Then, we again rewrite the equation in terms of the share of cake $\sigma_A(x)$ that $i = 1$ will get in this economy using the relationship $\sigma_A(x) = \frac{x_1^*}{2\mu(x)}$.

$$(\sigma_A(x) \cdot 2\mu(x))^{1-\epsilon} + (2\mu(x)(1-\sigma_A(x)))^{1-\epsilon} = 2\mu(x)^{1-\epsilon} \cdot \left(\{1 - \tilde{A}(x) \cdot (1 - 2^{\frac{-\epsilon}{1-\epsilon}})\}\right)^{1-\epsilon}$$

$$\sigma_A(x)^{1-\epsilon} + (1-\sigma_A(x))^{1-\epsilon} = 2^{\epsilon} \cdot \left(1 - \tilde{A}(x) \cdot (1 - 2^{\frac{-\epsilon}{1-\epsilon}})\right)^{1-\epsilon} \tag{10}$$

Thus, we derive an equation that we can use to solve for $\sigma_A(x) \in [0, 0.5]$ representing the share of cake that a poorer person in an equivalent two-person economy will receive.

However, this index has certain limitations as an inequality measure. Due to the structure of the final equation, $\sigma_A(x)$ is undefined for values of $\epsilon > 1$. This slightly limits its scope to be used as a complement to the Atkinson Index for high levels of inequality aversion. However, since $\sigma_A(x)$ can be calculated for $\epsilon = 1 - \delta$, it is an ideal complement to the Gini coefficient, which resembles the Atkinson Index at $\epsilon = 1$ since it gives equal weight to relative income disparities in both halves of the income distribution.

Additionally, though $\sigma_A(x)$ is highly intuitive and simple to understand, it is not as simple to calculate. Unfortunately, there cannot be a closed form solution for $\sigma_A(x)$. However, we can use numerical methods such as root-solving and apply it to real-world data to find this intuitive index for different economies.

5.2 The Intuitive Picture

We visualise the historical trends observed in India using our $\sigma_A(x)$ index and the Atkinson Index for $\epsilon = (0.25, 0.5, 0.75)$ using pie charts, demonstrating that the poorer person's perceived share of the cake increases as our inequality tolerance increases.

Let us take a moment to discuss the limitations/caveats involved with the use of $\sigma_A(x)$. The natural intuition behind our index comes at the cost of some granularity and statistical meaningfulness, as σ_A(x) abstracts away from the full income distribution, which other measures such as Gini and $A(x)$ retain.

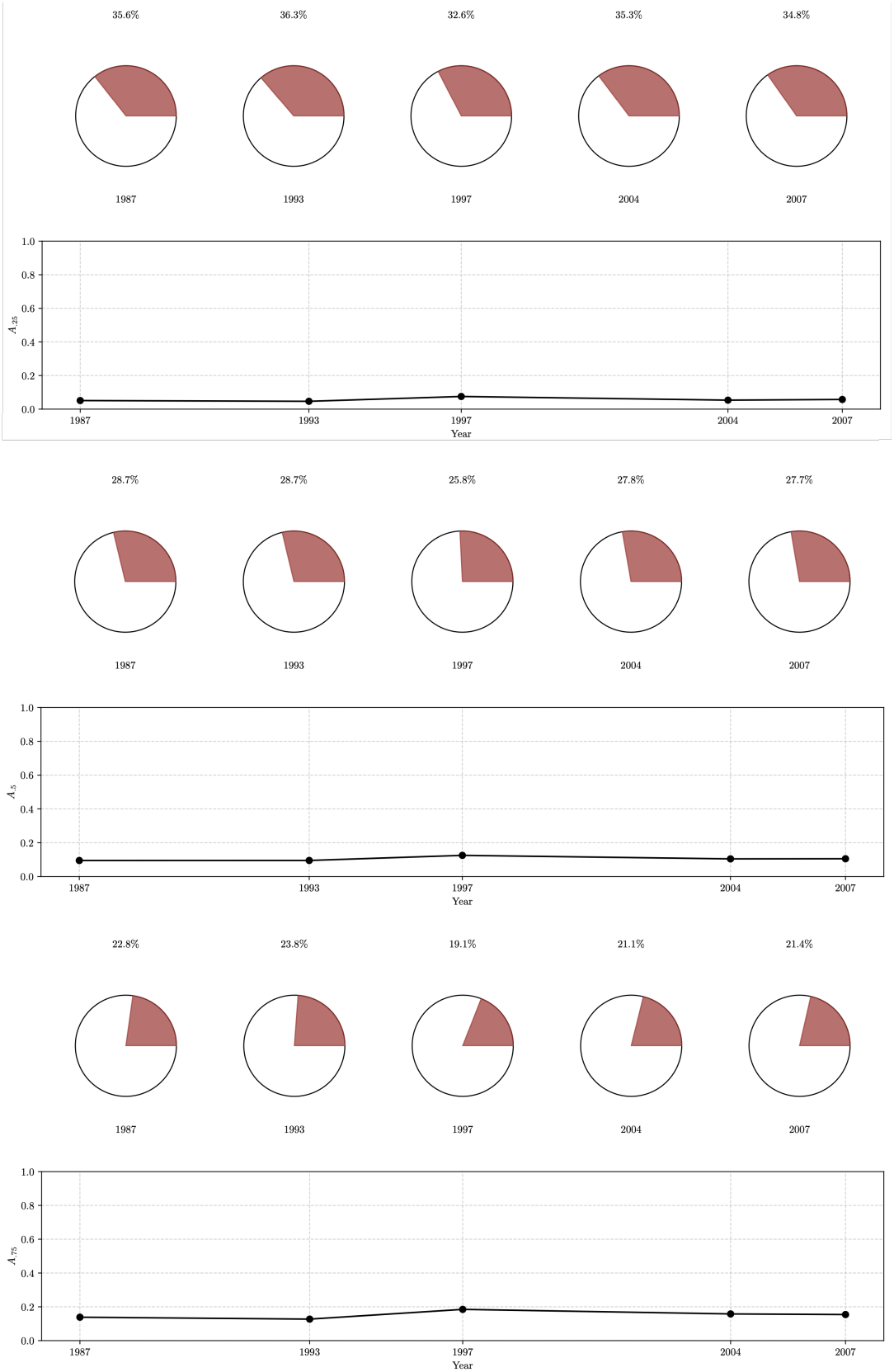


Figure 1: Charts Representing $\sigma_{.25}(x), \sigma_{.5}(x), \sigma_{.75}(x)$ and $A_{.25}(x), A_{.5}(x), A_{.75}(x)$ respectively[a]

[a]Since our analysis here is limited to India, we encourage the reader to explore these trends for other countries and regions using our method.

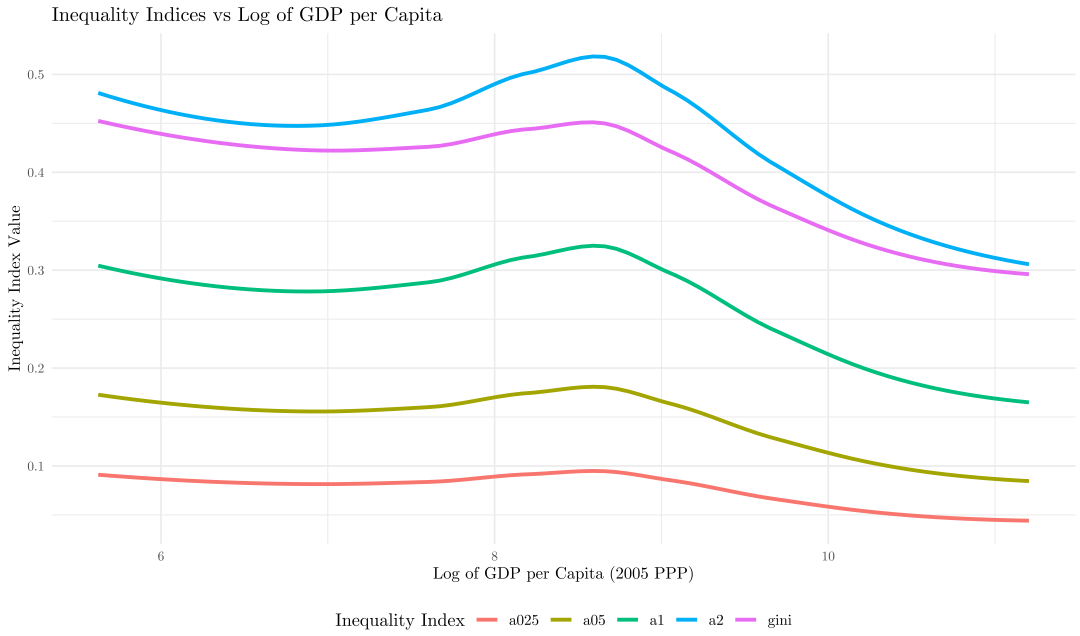


Figure 2: Inequality indices vs Log GDP per capita

5.3 Kuznets Hypothesis

The Kuznets Hypothesis[8] states that the relationship between economic development and inequality is an inverted-U, i.e., as development occurs, market forces first increase and then decrease inequality. Many income distribution datasets produce this inverted-U curve. However, this is often attributed to low data quality and/or an insufficient number of datapoints [9] along with other shortfalls of the hypothesis highlighted by Deininger and Squire (1998), including the fact that it vanishes under controls for Latin American countries and often doesn't hold at a country or region-specific level.

Due to the small size of our dataset, we expect a similar incomplete/unclear confirmation of the Kuznets Hypothesis without accounting for country or region-fixed effects. We do this by plotting the values of our inequality indices against log of GDP-PC (2005 PPP).

We find that our dataset and calculated inequality indices do seem to confirm the Kuznets Hypothesis. On adding $(1 - \sigma_{0.25})$ and $(1 - \sigma_{0.5})$ to the plot, we confirm our hypothesis and see a similar trend.

[8] Kuznets, S. *Economic Growth and Income Inequality.* American Economic Review 45 (March): 1–28. 1955.

[9] Deininger K., Squire L. *New Ways of Looking at Old Issues: Inequality and Growth.* Journal of Development Economics. 57 (2): 259–287. 1998.

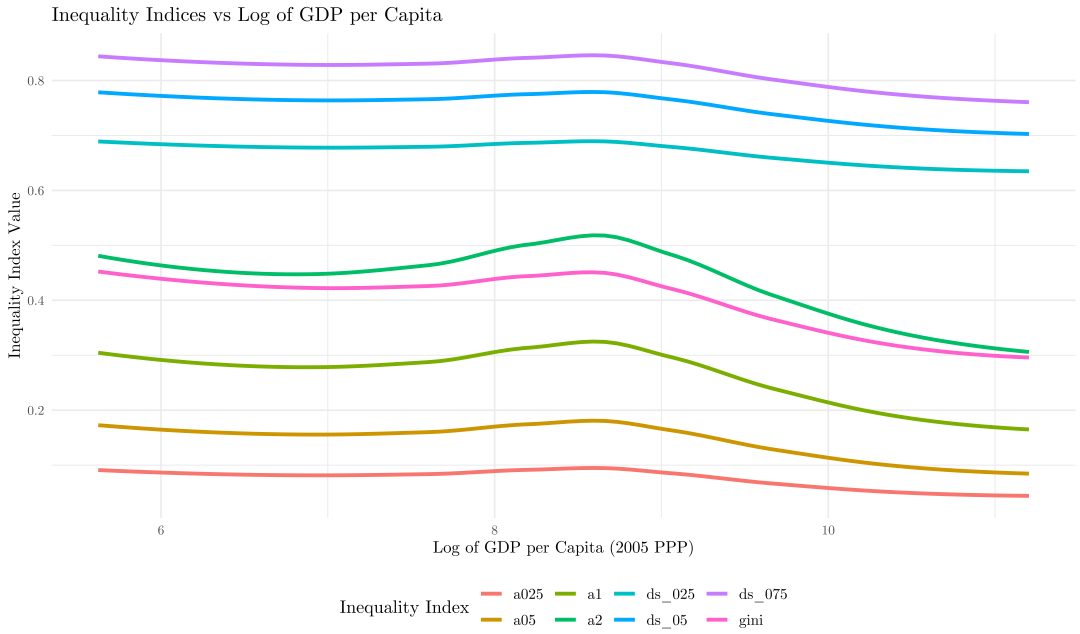


Figure 3: Inequality indices vs Log GDP per capita

Table 4: Average Difference Between Gini and Atkinson Index at $\epsilon = 2$ for Different Income Groups

Income Classification	**Income Group**	**Average Difference**
World Poverty Line	GDP $<$ 456.25	-0.03642
Low Income	456.25 $<=$ GDP $<=$ 733.86	-0.02724
Lower Middle Income	733.86 $<$ GDP $<=$ 2893.79	-0.02723
Upper Middle Income	2893.79 $<$ GDP $<=$ 8976.19	-0.06479
High Income	GDP $>$ 8976.19	-0.03655

5.4 The Limitations of the Gini Coefficient

Having explored $\sigma_A(x)$, we come back to the Atkinson Index. We observe a difference between the Gini and$A(x)$ at $\epsilon = 2$, i.e. a relatively high level of inequality aversion and sensitivity to inequalities within the lower end of the income distribution. To test whether this difference is significant and whether there is a relationship between this difference and the income groups that a country belongs to, we run a ttest.

We find that all of these differences are statistically significant at any conventional alpha. However, we also notice a trend across income groups, i.e. for a richer country, it is likelier for the Gini coefficient to be smaller than the Atkinson Index at $\epsilon = 2$.

This suggests that the Gini coefficient, the most popular measure used to compare inequality levels across countries, underestimates richer countries' inequality levels due to its lack of

Table 5: T-test results for difference between Gini And Atkinson Index at $\epsilon = 2$ for different income groups

Income Classification	**Income Group**	**Average Difference**	**P Value**
World Poverty Line	GDP $<$ 456.25	-0.03642	0.0047174660
Low Income	456.25 $<=$ GDP $<=$ 733.86	-0.02724	0.0020704470
Lower Middle Income	733.86 $<$ GDP $<=$ 2893.79	-0.02723	0.0000000038
Upper Middle Income	2893.79 $<$ GDP $<=$ 8976.19	-0.06479	0.0000000000
High Income	GDP $>$ 8976.19	-0.03655	0.0000000000

consideration for social welfare at slightly higher levels of inequality aversion.

6 Conclusion

6.1 Applications of $\sigma_A(x)$

We derive the $\sigma_A(x)$ index for any income distribution (x). We believe that this measure of inequality will be helpful for the layman as a complement to conventional measures like the Gini coefficient or the Atkinson Index, as it provides a highly intuitive understanding of inequality while having welfare considerations baked into it.

Additionally, we believe that impact evaluations for welfare programmes, especially progressive tax or transfer programmes will be made simpler for policymakers by using $\sigma_A(x)$ as a metric, e.g. we posit that if the share of cake going to the poorer person in an equivalent two-person economy doesn't increase, then a targeted transfer likely wasn't successful in both, reducing inequality and improving welfare. Comparing the conclusions derived using $\sigma_A(x)$ with widely accepted existing evaluations of progressive tax/transfer programmes would help check its reliability as a metric.

Some other ideas we have involve the use of σ_A(x) as a metric to study inequality trends before and after major socioeconomic shocks like financial crises, trade liberalisation, or technological disruption. It may also be useful in an instructive manner, to generate interest in researchers to take up the Atkinson Index.

6.2 The Atkinson Index

Due to the moral and econometric limitations we have highlighted within the Gini coefficient, we propose that no inequality measure should have monopoly over economic research. Hence, we want to invite increased use of the Atkinson class of inequality indices and their many unique properties, complemented by our $\sigma_A(x)$ index for a richer and more accessible understanding of the structure of inequality in an economy.

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Does rising stock market wealth translate into higher consumption? Evidence from the U.S. and emerging market economies

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Abstract

This paper investigates the extent to which stock market wealth influences household consumption, drawing evidence from both the United States and developing economies. Grounded in the theoretical frameworks of the Life-Cycle Hypothesis and the Permanent Income Hypothesis, the study explores how asset price changes—particularly in equities—affect consumption decisions over both the short and long run. In the U.S. context, empirical results from studies such as Ludvigson and Steindel (1999) show a positive but time-varying marginal propensity to consume (MPC) out of stock market wealth, with stronger effects among wealthier households. Using advanced econometric methods like Dynamic OLS and error-correction models, the U.S. evidence confirms a modest but significant long-run relationship between stock market wealth and consumer spending, though short-term effects remain weak. In contrast, recent empirical evidence from Singh (2022) reveals that in developing and emerging market economies (EMEs), the stock wealth effect is generally weaker or statistically insignificant, particularly in less financially developed countries. Using panel data across 20 EMEs from 1996 to 2019, Singh finds that housing wealth has a robust positive effect on consumption, while stock market wealth does not, largely due to low stock market participation, high return volatility, and limited access to credit. However, in countries with deeper financial systems, the stock wealth effect becomes positive and statistically significant, highlighting the importance of financial infrastructure in mediating wealth-consumption linkages. The findings suggest that while stock market wealth can influence household consumption in both advanced and developing economies, the strength and stability of this relationship are highly contingent on institutional and market development. As EMEs continue to integrate financially and broaden equity participation, the stock market's role in shaping consumption patterns is likely to

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grow. This study contributes to the understanding of heterogeneous wealth effects across economic contexts and offers policy-relevant insights into how financial development can enhance the transmission of wealth into aggregate demand.

Keywords: Stock Wealth, Consumption, Emerging Economies, Marginal Propensity to Consume, Financial Development

JEL Classification: E21, G10, O16, D12

1 Introduction

The relationship between wealth and consumer behaviour has long been central to macroeconomic theory. Economists often refer to the "wealth effect" to describe how rising asset values—such as those from equities or real estate—tend to encourage greater consumption. This shift in consumer behaviour is not merely rooted in disposable income but is also shaped by psychological confidence. When households perceive themselves to be wealthier, they are more likely to spend, feeling more financially secure about the future. Booms in asset markets, especially in equities and housing, have historically coincided with surges in personal consumption, while market contractions often precede reductions in spending.

Foundational theories in economics, such as the life-cycle hypothesis by Ando and Modigliani, and Friedman's permanent income hypothesis, support this behavioural pattern. The former posits that individuals aim to smooth consumption over their lifetime based on expected income and accumulated wealth. The latter emphasizes that long-term income expectations, rather than short-term earnings, primarily influence consumption patterns. Both frameworks imply that if rising asset prices are perceived as permanent, they may enhance expected lifetime resources and thus prompt increased consumption.[2]

In the U.S., empirical data from the 1990s—when household wealth grew significantly, largely due to rising equity values—demonstrate the practical relevance of these theories. During this time, many households saw modest investments transform into substantial portfolios, increasing the number of households crossing the millionaire threshold.[3]

Despite such insights, most empirical research on wealth effects remains concentrated in high-income economies. In contrast, emerging markets like India, Brazil, and South Africa have received less attention. As these nations undergo financial deepening and broader asset ownership, it becomes increasingly important to understand how asset price changes impact household consumption. This study, therefore, extends the existing literature by examining stock market wealth effects in both the U.S. and emerging market contexts.

[2]Robert J. Barro, *Macroeconomics*, 4th ed. (Cambridge: MIT Press, 1997), 107.
[3]Milton Friedman, *A Theory of the Consumption Function* (Princeton: Princeton University Press, 1957).

2 Literature Review

The relationship between rising stock market wealth and household consumption has been extensively studied within the intertemporal consumption framework, notably the life-cycle and permanent income hypotheses. An unanticipated increase in household wealth, driven by stock market appreciation or "wealth surprises," is posited to alter consumption trajectories as households adjust their future spending plans in response to augmented lifetime resources.

Formally, in a standard life cycle model, a representative consumer chooses the consumption path (C_t) to maximize expected utility (u) over his life cycle:

$$\max E_t \left[\sum_{t=0}^{n} (1+\delta) x^{-t} u(C_t) \right] \tag{11}$$

Following the intertemporal decision-making rule, δ is the rate of time preference, i.e., the rate of interest on savings required to compensate the consumer for foregoing current consumption in favour of future consumption. The above utility maximization is subject to the following constraint where y is real disposable income and w is real household wealth.

$$w_{t+1} = (1+r)\big[w_t + (y_t - c_t)\big] \tag{12}$$

Thus, given the budget constraint, the asset at the end of each period equals the asset at the beginning of the period plus savings, which yields an interest rate (r). The consumption path can be derived based on the first-order condition.

$$C_t = \left(\frac{r}{1+r}\right) w_t + \left(\frac{r}{1+r}\right) + \sum_{k=0}^{t=n} (1+r)^{-k} E_t Y_{t+k} \tag{13}$$

The equation implies that consumption in period t (C_t) is determined by the stock of non-human (w_t) and human wealth (y_t). In other words, consumption is a function of assets held by consumers at time t and the total of current and discounted expected future income stream. Thus, the propensity to consume out of total wealth is $r/(1+r)$.

This foundational insight is rooted in Friedman's (1957) permanent income hypothesis, which postulates that consumption decisions are based on an individual's lifetime expected income

rather than current income alone. Modigliani and Brumberg's (1954) life-cycle hypothesis further elaborates that consumption smoothing occurs over the lifecycle to optimize utility, considering anticipated income changes. Ando and Modigliani (1963) formalized this framework by explicitly modeling consumption as a function of accumulated wealth and expected income.[4]

Subsequently, the life cycle model was extended to consider the factors influencing household behaviour such as lags in responding to income or wealth changes due to behavioural constraints; inability to borrow fully against expected changes in wealth (Wilcox, 1990); hedging motives against future uncertainties; and bequest motives persuading households to save rather than consume incremental income or wealth (Davis and Palumbo, 2001).[5]

The life cycle model suggests that in the absence of wealth surprises, wealth could vary considerably over time; however, consumer spending will be reasonably stable. However, in situations where households experience an unexpected increase in their wealth, they will revise their spending plans with higher consumption in the future. Thus, household spending should respond to unexpected changes in wealth, such as from stock-market surprises and housing booms and busts. Surprise increases in household wealth generate higher levels of lifetime resources and engender higher levels of spending over the remainder of the household's planning period.

The evolving empirical literature has adapted the life cycle framework to build models that quantify the relationship. Carroll and Samwick (1997) empirically tested the permanent income and life cycle hypotheses, finding that wealth accumulation and consumption are closely linked over time, especially in response to financial asset changes.[6] Poterba and Samwick (1995) highlighted that increases in stock market wealth positively affect household consumption, with households holding equities exhibiting greater sensitivity to market fluctuations.[7]

[4]Franco Modigliani and Richard Brumberg, "Utility Analysis and the Consumption Function: An Interpretation of Cross-Section Data," in *Post-Keynesian Economics*, ed. Kenneth Kurihara (New Brunswick: Rutgers University Press, 1954); Albert Ando and Franco Modigliani, "The 'Life Cycle' Hypothesis of Saving: Aggregate Implications and Tests," *American Economic Review* 53, no. 1 (1963): 55–84.

[5]Morris A. Davis and Michael G. Palumbo, "A Primer on the Economics and Time Series Econometrics of Wealth Effects," Finance and Economics Discussion Series, Federal Reserve Board, 2001.

[6]Christopher D. Carroll and Andrew A. Samwick, "The Nature of Precautionary Wealth," *Journal of Monetary Economics* 40, no. 1 (1997): 41–71.

[7]James M. Poterba and Andrew A. Samwick, "Stock Ownership Patterns, Stock Market Fluctuations, and Consumption," *Brookings Papers on Economic Activity* 1995, no. 2 (1995): 295–372.

Further, Dynan and Maki (2001) found that capital gains from stock market appreciations significantly influence short-term consumption, particularly for wealthier households with substantial stock holdings.[8] In contrast, Ludvigson and Steindel (1999) cautioned that while the relationship exists, its magnitude may vary over time and across demographic groups.[9]

More recent studies extend these findings to emerging economies. For instance, Kapoor and Ravi (2020) examined Indian households and found that increases in equity wealth led to increased consumption, albeit with lower marginal propensity compared to developed nations. They argue that financial literacy, market access, and investment culture all mediate the strength of the wealth effect in such contexts.

Moreover, Aizenman and Jinjarak (2010) showed that in countries with less developed capital markets, the transmission of stock market gains to consumption is weaker, often due to credit constraints, limited participation in equity markets, and lower consumer confidence.[10] Nonetheless, as emerging markets develop, the responsiveness of consumption to financial wealth is expected to grow.

In summary, while theoretical models suggest a direct and rational relationship between stock market wealth and consumption, empirical results show variation based on market maturity, institutional development, and household characteristics.

3 Historical Context and Composition of Stock Market Wealth in the U.S.

While theoretical and empirical literature offers a robust foundation for understanding the wealth effect on consumption, situating this within a historical context enhances our comprehension. The U.S. economy in the 1990s offers a salient case study, wherein stock market-driven wealth gains significantly shaped household consumption behavior.

[8] Karen E. Dynan and Dean M. Maki, "Does Stock Market Wealth Matter for Consumption?" Finance and Economics Discussion Series, Federal Reserve Board, 2001.

[9] Sydney Ludvigson and Charles Steindel, "How Important is the Stock Market Effect on Consumption?" *Federal Reserve Bank of New York Economic Policy Review* 5, no. 2 (1999): 29–51.

[10] Aizenman, J., & Jinjarak, Y. (2010). Stock Market Wealth and Consumption. *Journal of International Money and Finance*, 29(4), 557–574.

3.1 Stock Market Boom of the 1990s

The 1990s in the U.S. marked a period of exceptional stock market performance. Between 1989 and 1999, the real net worth of American households increased by approximately $15 trillion—a rise of over 50 percent in real terms. A significant portion of this growth was driven by rising stock prices, with corporate equities accounting for over 60% of the total increase in household wealth.

As equity markets soared, more Americans crossed wealth thresholds that previously seemed unattainable. For instance, the number of U.S. households with net worths exceeding $1 million increased from 3 million in 1995 to 4.5 million by 1998, and likely surpassed 5 million by 2000.[11] This widespread appreciation in stock market wealth not only enhanced financial positions but also encouraged greater consumer confidence and spending.

Figure 1 illustrates that sustained gains in the stock market during the 1990s significantly increased household net worth. As wealth rose, consumer confidence and expenditures also climbed, suggesting a possible causal link.

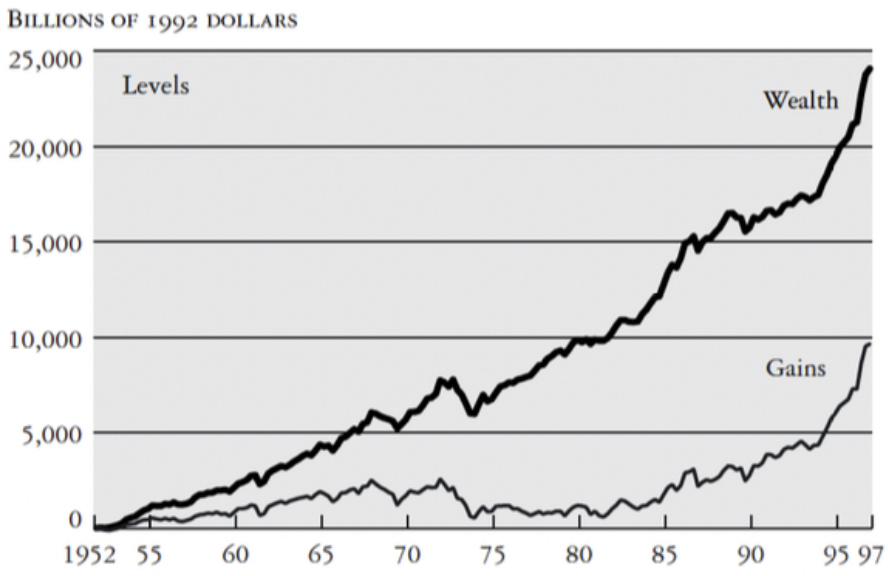


Figure 1: Growth in Wealth and Accumulated Stock Market Gains.
Source: Board of Governors of the Federal Reserve System

This linkage is explored further in Figure 2, which plots the wealth-to-disposable-income ratio against the personal saving rate. Over the 1990s, the wealth-to-income ratio increased sharply,

[11] ibid

largely driven by rising stock valuations. At the same time, the personal savings rate declined markedly. This inverse relationship supports the notion of a strong wealth effect—wherein households, feeling wealthier due to capital gains, reduce their rate of saving and increase consumption, even when income levels remain stable.

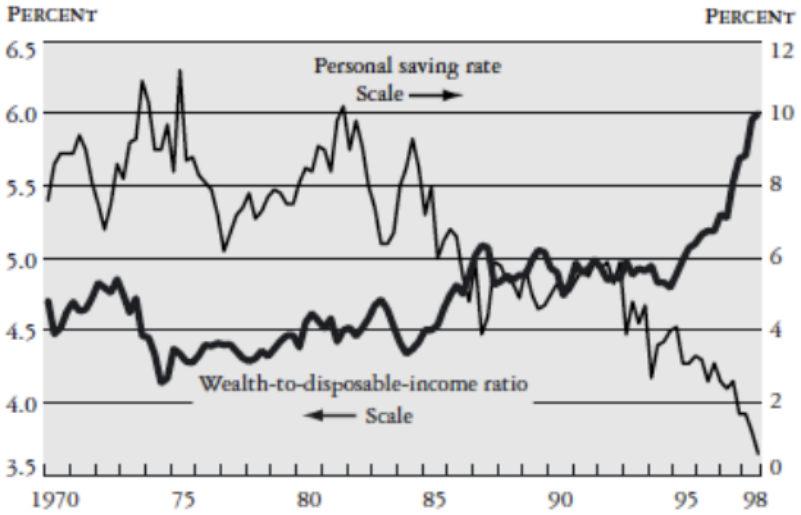


Figure 2: Wealth-to-Disposable-Income Ratio and Personal Saving Rate, 1989–1999.
Source: U.S. Department of Commerce, Bureau of Economic Analysis

3.2 Changes in Wealth Composition: Table 1

The boom also changed the composition of household wealth. According to Table 1, based on Federal Reserve data and adapted from Poterba (2000), corporate equities became a significantly larger share of household net worth by 1999. While real estate and tangible assets continued to hold importance, corporate stock holdings grew by 262%, far outpacing the growth of other asset classes like non-equity financial assets (38%) and tangible assets (14%).

Table 1: Composition of Household Net Worth, December 1989 and December 1999 ($1999 billion).
Adapted from Poterba (2000)

Asset Category	**December 1989**	**December 1995**	**December 1999**
Tangible Assets	12,183.5	11,796.2	13,940.9
Financial Assets Excluding Equities	15,634.5	17,168.8	21,616.8
Market Value of Equities	3,682.8	6,730.4	13,331.5
Liabilities	4,542.2	5,453.5	6,840.9
Net Worth	26,958.5	30,241.8	42,048.2

Source: Board of Governors of the Federal Reserve System

This exceptional growth rate in equity wealth was unprecedented since the early 1950s and underscored the importance of stock market movements in shaping household financial conditions.

3.3 Inequality in Wealth Distribution: Table 2

Despite the aggregate rise in net worth, wealth gains were not evenly distributed across income groups. Table 2, derived from the 1998 Survey of Consumer Finances, illustrates this disparity. The top 0.5% of households held over 40% of all corporate equity, while the bottom 80% owned just over 4%.

This concentration of stock ownership implies that the direct effects of stock market changes on consumption are mostly experienced by wealthy households. For the majority of Americans—who either held no stocks or had relatively small holdings—rising stock prices had limited influence on their spending behavior.

Table 2: Percentage of Different Assets Owned by Households with Substantial and More Limited Holdings, 1998.
Adapted from Poterba (2000)

Pct. of Owners	**Common Stock Excl. Pensions**	**All Common Stock**	**Non-Equity Fin. Assets**	**Housing Equity**	**Net Worth**
Top .5 Percent	41.4	37.0	24.2	10.2	25.6
Next .5 Percent	11.8	10.7	7.8	4.6	8.4
Next 4 Percent	27.7	27.2	26.2	20.5	23.4
Next 5 Percent	10.3	11.3	14.0	15.4	11.4
Next 10 Percent	7.2	9.8	13.9	20.1	12.8
Bottom 80 Percent	1.7	4.1	14.0	29.3	18.5

Source: 1998 Survey of Consumer Finances

This concentration of stock ownership implies that the direct effects of stock market changes on consumption are mostly experienced by wealthy households. For the majority of Americans—who either held no stocks or had relatively small holdings—rising stock prices had limited influence on their spending behavior.

3.4 Estimating the Consumption Response: Table 3

To quantify how changes in wealth may translate into changes in consumption, Poterba (2000) used a life-cycle consumption framework assuming no bequest motive. The model estimates how much current annual consumption would increase for every additional dollar of wealth, depending on the consumer's planning horizon and the after-tax rate of return.

This is derived from a basic annuity model within the life-cycle hypothesis framework:

$$\Delta C = \frac{r}{1 - (1 + r)^{n-T}} \tag{14}$$

Where ΔC represents the change in annual consumption per dollar of wealth gained, r is the after-tax real interest rate and T is the planning horizon (in years).

For example: a 30-year horizon and $r = 0.03$: $\Delta C \approx 0.051$. This suggests that households without bequest motives would optimally increase their annual consumption by about 5.1 cents

for every $1 of new wealth.

Table 3: Change in Annual Consumption per $1 Wealth Increase Assuming No Bequest Motive

	Household Planning Horizon		
After-Tax Rate of Return	**15 Years**	**30 Years**	**45 Years**
.01	.074	.038	.027
.03	.081	.050	.040
.05	.092	.062	.053
.07	.103	.075	.069

Source: 1998 Survey of Consumer Finances

Table 3 shows that longer planning horizons lead to smaller annual changes in consumption, as the wealth is spread over a longer period and higher interest rates increase the marginal effect on consumption, since future consumption is discounted more heavily.

These theoretical findings are broadly consistent with empirical results. Ludvigson and Steindel (1999), for instance, estimated marginal propensities to consume (MPCs) from stock wealth ranging between 2 and 7 cents per dollar.[12] These results reinforce that while stock market wealth can influence aggregate consumption, the magnitude of the effect is strongly correlated with the concentration of equity holdings among high-wealth households.

4 Data and Methodology

To empirically investigate the relationship between stock market wealth and consumer spending, Ludvigson and Steindel (1999) employ quarterly U.S. macroeconomic data covering a sample period from 1953 to 1998.[13] The primary variables of interest include real personal consumption expenditures (PCE), household net worth—disaggregated into equity wealth, non-equity financial assets (such as bonds and deposits), and tangible assets (such as real estate and durable goods)—and real disposable personal income. All variables are deflated using the per-

[12]Ludvigson and Steindel, "How Important is the Stock Market Effect on Consumption?"

[13]Lydney Ludvigson and Charles Steindel, "How Important Is the Stock Market Effect on Consumption?" *Federal Reserve Bank of New York Economic Policy Review* 5, no. 2 (1999): 29–51.

sonal consumption expenditures deflator to express them in real terms. The data are drawn from multiple official sources: the National Income and Product Accounts (NIPA) and Flow of Funds Accounts, both published by the U.S. Department of Commerce and the Federal Reserve, as well as the University of Michigan's Survey of Consumers.

The empirical strategy includes estimating marginal propensities to consume out of different types of wealth using vector autoregression (VAR) models, as well as cointegration techniques to examine long-run equilibrium relationships among consumption, income, and wealth. In the VAR framework, changes in consumption are regressed on lagged values of itself and the different components of household wealth, controlling for income and other macroeconomic factors. Additionally, the study employs error-correction models (ECMs) derived from cointegrating relationships to capture short-run dynamics.

4.1 Traditional Life-Cycle Consumption Model

The initial approach is based on the traditional life-cycle consumption model, where real consumer expenditure in a given period is modelled as a function of income (Y), Stock market wealth (SW), and Non-stock market wealth (NW).

$$C_t = \sum_{i=0}^{3} \delta_i Y_{t-i} + \sum_{i=0}^{3} \xi_i SW_{t-i} + \sum_{i=0}^{3} \mu_i NW_{t-i} + \varepsilon_t \tag{15}$$

This model assumes that households plan consumption based on current economic resources, including labor income and accumulated wealth, without addressing the underlying statistical properties of the variables (such as trends or reversals). The marginal propensities to consume (MPCs) out of income and each type of wealth are directly estimated via ordinary least squares (OLS).

4.2 Dynamic Ordinary Least Squares (DOLS)

To correct for endogeneity and nonstationarity, we implement the Dynamic OLS (DOLS) method, as proposed by Stock and Watson (1993). This approach augments the cointegrating regression with leads and lags of the first differences of the regressors to correct for endogeneity

and serial correlation:

$$c_t = \alpha + \beta_l w_t + \delta_l y_t + \sum_{i=-3}^{3} \beta_{l,i}\, \Delta w_{t+i} + \sum_{i=-3}^{3} \delta_{l,i}\, \Delta y_{t+i} + u^*_{l,t} \tag{16}$$

where c_t, w_t, and y_t denote the log of consumption, wealth, and labor income, respectively, and Δ is the first difference operator. The inclusion of leads and lags of Δw_t and Δy_t ensures that parameter estimates are not biased due to endogeneity or serial correlation.

In the estimation, we consider total net worth rather than separating stock market and non-stock-market components, consistent with theoretical models that treat wealth as a unified stock of resources. Moreover, the focus is on consumption of nondurables and services—excluding durables such as automobiles and household appliances—to better capture the flow of utility-generating consumption. Durables, representing investments in the capital stock, are conceptually distinct and may exhibit different dynamic properties in response to wealth changes.

Finally, although our primary interest lies in the effect of dollar changes in wealth on consumption, we estimate the DOLS model in logarithmic form due to the approximate log-linear relationship observed in the time-series data and to mitigate potential heteroskedasticity.

4.3 Error-Correction Model (ECM)

To capture short-run dynamics and deviations from the long-run relationship identified in DOLS, we estimate a restricted vector autoregression (VAR) in first differences with an error-correction term. Let

$$\Delta \mathbf{x}_t = (\Delta c_t,\, \Delta w_t,\, \Delta y_t)'$$

denote the vector of log first differences of consumption, wealth, and labor income, respectively. The model takes the following form:

$$\Delta \mathbf{x}_t = \mu + \alpha\Big(c_{t-1} - \hat{\beta}_l w_{t-1} - \hat{\delta}_l y_{t-1}\Big) + \sum_{j=1}^{k} \Gamma_j\, \Delta \mathbf{x}_{t-j} + \varepsilon_t \tag{17}$$

where:

- μ is a vector of intercept terms,

- α is a vector of error-correction coefficients,
- Γ_j are matrices of short-run dynamic coefficients for each lag j,
- $\hat{\beta}_l$ and $\hat{\delta}_l$ are the previously estimated cointegrating coefficients from the dynamic OLS procedure, and
- $\left(c_{t-1} - \hat{\beta}_l w_{t-1} - \hat{\delta}_l y_{t-1}\right)$ is the **error-correction term**, representing the deviation from the long-run equilibrium in the previous period.

This formulation explicitly accounts for the possibility that consumption, wealth, and labor income may temporarily diverge from their shared long-run trend due to short-run shocks, but subsequently adjust toward equilibrium. The inclusion of the error-correction term ensures that long-run information is incorporated into the short-run dynamics, thereby improving the model's structural coherence and empirical relevance. Such an error-correction model is appropriate when the underlying variables are individually nonstationary but cointegrated, indicating the existence of a stable long-term relationship. In contrast, if no such cointegration exists, an unrestricted VAR in first differences would be required. By exploiting the cointegration property, the present framework allows for more efficient estimation of both short-term responses and the speed of adjustment to long-run equilibrium.

5 Results

The empirical results across the three models provide a comprehensive understanding of the relationship between wealth from the stock market and consumption. In the traditional life-cycle consumption model, the marginal propensity to consume (MPC) out of income ranges from 0.568 to 1.015, with most estimates falling between 0.7 and 0.8, consistent with macroeconomic theory. The MPC out of stock market wealth is positive but highly unstable across time, ranging from 0.021 in the 1986–1997 subperiod to 0.106 during 1976–1985, with a full-sample estimate of 0.040, indicating that 4 cents of every additional dollar in stock wealth is spent.

Table 4: Results from the Traditional Life Cycle Model

	1	**2**	**3**	**4**	**5**	**6**	**7**
Independent	1953:1	1953:1	1976:1	1986:1	1953:1	1968:1	1983:1
	–1997:4	–1975:4	–1985:4	–1997:4	–1967:4	–1982:4	–1997:4
Variable							
Income (Y)	0.731	0.711	0.568	1.015	0.684	0.832	0.822
	(0.067)	(0.059)	(0.195)	(0.077)	(0.091)	(0.141)	(0.074)
Stock mkt. wealth (SW)	0.040	0.026	0.106	0.021	0.030	0.023	0.042
	(0.009)	(0.010)	(0.041)	(0.011)	(0.018)	(0.019)	(0.010)
Non-stock mkt. wealth (NW)	0.038	0.043	0.069	−0.027	0.049	0.012	0.016
	(0.017)	(0.015)	(0.048)	(0.017)	(0.020)	(0.036)	(0.018)
Serial corr. coeff.	0.937	0.781	0.937	0.755	0.800	0.886	0.809
	(0.030)	(0.090)	(0.069)	(0.097)	(0.094)	(0.069)	(0.091)
Std. error of regression	70.7	59.8	86.7	65.7	41.4	84.7	76.2
Sum sq. residuals	830835	279012	202961	150994	78739	336836	272807
Likelihood ratio test:							
Statistic			48.690			33.668	
Probability			0.0045			0.1436	

Figure 3 displays rolling regression estimates of the MPC over time, differentiating between three sources of wealth: (1) Disposable Income, (2) Stock Market Wealth, and (3) Non-Stock-Market Wealth. The top panel confirms the relatively stable and high MPC out of income, while the middle panel shows that the MPC from stock market wealth is smaller and more volatile. The bottom panel captures the dynamic effects of other forms of wealth. Dotted bands represent ± 1 standard deviation intervals.

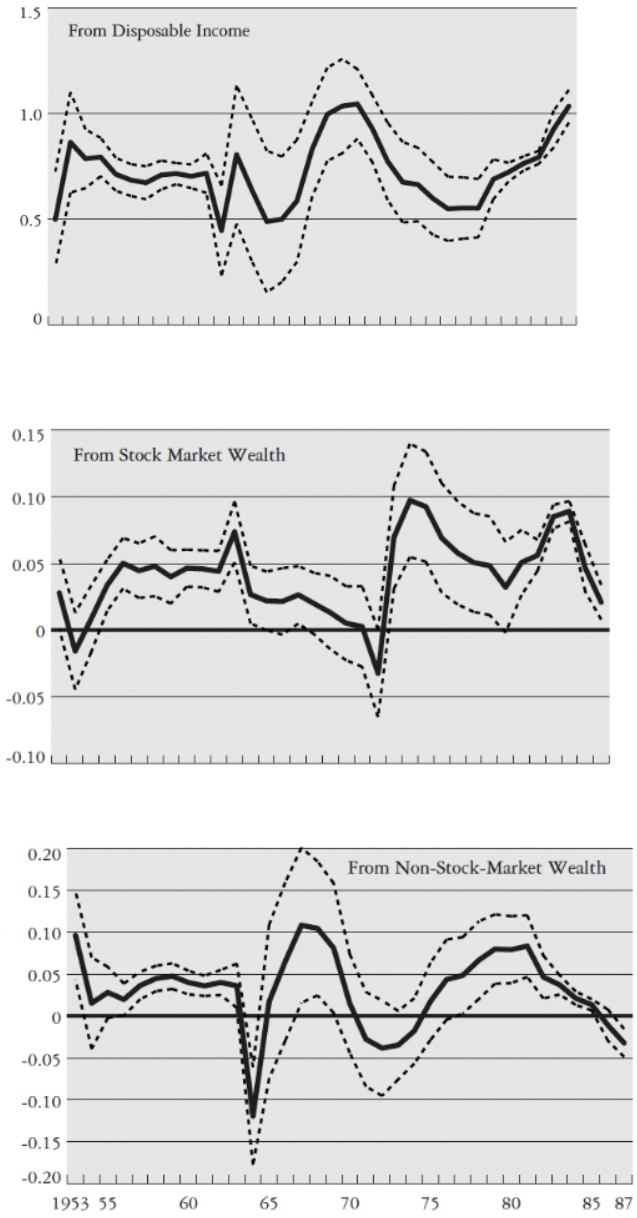


Figure 3: Marginal Propensity to Consume (Rolling Regression Estimates).
Top panel: from Disposable Income. Middle: from Stock Market Wealth. Bottom: from Non-Stock-Market Wealth. Dotted bands: ± 1 *std. dev.*

Table 5 given below offers a range of estimates for how the increase in stock market wealth between 1994 and 1997 influenced consumer spending levels in 1997. These figures are derived by applying marginal propensities to consume—obtained from columns 1, 3, and 4 of Table 4—to the overall real increase in household stock market wealth during that period. Depending on the assumed marginal propensity to consume, the dollar impact on consumption ranges from $87 billion to $416 billion—representing 1.8% to 8.9% of total consumer spending in

1997. This reinforces the potential macroeconomic significance of wealth-driven consumption effects.

Table 5: Estimated Impact of 1994–97 Stock Market Rise on 1997 Consumer Spending

Propensity to Consume	**Dollar Impact of Wealth Increase on Real Spending**	**Percentage of 1997 Consumer Spending**
0.040 (1953:1–1997:4)	$166 billion	3.4
0.106 (1976:1–1985:4)	$439 billion	8.9
0.021 (1986:1–1997:4)	$87 billion	1.8

Source: U.S. Department of Commerce, Bureau of Economic Analysis

However, the traditional model is limited by statistical issues such as nonstationarity and endogeneity. Addressing these concerns, the Dynamic OLS (DOLS) model produces more (Table 6) robust and stable long-run estimates . Over the full sample, the marginal propensity to consume (MPC) out of wealth is estimated at 0.046, while the MPC out of labor income is 0.72, with both coefficients statistically significant. These values indicate that a $1 increase in wealth leads to an increase of approximately 4 to 5 cents in long-run consumption. However, closer inspection revealed that much of the instability in the estimates was concentrated in the early subperiod, particularly during the post–Korean War years. To address this issue, the sample was re-estimated beginning in the first quarter of 1957, excluding the pre-1957 data. This adjustment notably improved the stability of the estimates in certain dynamic OLS specifications. The revised sample maintained similar results—an MPC of 0.04 for wealth and 0.72 for labor income—suggesting that the long-run relationship is not driven by anomalies in the earlier part of the data.

Table 6: Results from the DOLS Model

	MPC out of Wealth		**MPC out of Labor Income**	
Sample Period	**Log**	**Level**	**Log**	**Level**
1953:1–1997:1	0.291*	0.046	0.605*	0.718
	(8.10)		(18.09)	
1953:1–1967:4	0.380*	0.072	0.500*	0.615
	(3.78)		(5.20)	
1968:1–1982:4	0.155	0.031	0.729*	0.861
	(1.58)		(11.32)	
1983:1–1997:1	0.151*	0.024	0.764*	0.907
	(3.69)		(12.13)	

* denotes statistical significance. t-statistics in parentheses.

Finally, the error-correction model, which incorporates short-run fluctuations and long-run equilibrium, reveals that stock market wealth has little short-run predictive power for consumption growth, as lagged changes in wealth are statistically insignificant (p = 0.41). Moreover, the error-correction term for consumption does not significantly affect short-run adjustments, whereas wealth itself adjusts strongly to restore equilibrium. Together, these findings suggest that wealth has a stable long-run effect on consumption but limited short-term influence, particularly in the case of stock market wealth.

Table 7: Results from the Error Correction Model

	Equation		
	Δc_t	Δw_t	Δy_t
Joint significance of			
$\Delta c_{t-i},\ i = 1 \ldots 2$	0.04	0.08	0.04
$\Delta y_{t-i},\ i = 1 \ldots 2$	0.18	0.08	0.95
$\Delta w_{t-i},\ i = 1 \ldots 2$	0.61	0.08	0.39
Coefficient on error-correction term			
$c_{t-1} - \hat{\beta}_l w_{t-1} - \hat{\delta}_l y_{t-1}$	-0.001	0.476	0.113
(p-value)	(0.99)	(0.00)	(0.13)
Adjusted R^2	0.11	0.14	0.05

6 Developing Countries: Stock Market Wealth and Consumption

The relationship between stock market wealth and household consumption, while well-documented in advanced economies, remains underexplored in developing and emerging market economies (EMEs). Singh (2022) addresses this research gap by empirically examining the wealth effects of both housing and stock prices on consumption across 20 large EMEs over the period 1996:Q1 to 2019:Q4.[14] Using a comprehensive panel dataset and advanced estimation techniques, the study offers important insights for adapting frameworks established in developed economies—like the United States—to structurally distinct developing contexts.

Singh highlights that in EMEs, financial systems are typically less developed: mortgage and equity markets are thinner, and household access to these markets is limited. This institutional backdrop suggests that wealth effects may operate differently in EMEs compared to advanced economies, where broad-based stock ownership and mature credit systems facilitate the trans-

[14] Abhishek Singh, "Do Housing and Stock Prices Affect Consumption in Emerging Market Economies?" *IMF Economic Review* 70, no. 3 (2022): 529–567.

mission of asset price changes to consumption.

To investigate these relationships, Singh employs several econometric approaches—Dynamic Panel Data (DPD), Fixed Effects (FE), and Pooled Mean Group (PMG)—to assess whether and how wealth affects consumption, with particular attention to the differential impacts of housing and stock market wealth.

6.1 Empirical Evidence and Regional Heterogeneity

The empirical results from the PMG estimator reveal that housing wealth exerts a statistically significant and economically meaningful effect on household consumption in EMEs. Specifically, a 1 percent increase in real house prices is associated with a 0.09 percent increase in per capita consumption expenditure.[15] Regionally, the effect is strongest in Europe (0.12) and Latin America (0.11), while Asia displays a more modest coefficient of 0.05.[16] These findings support the hypothesis that housing wealth, due to its broader ownership and perceived durability, generates a greater marginal propensity to consume (MPC) than financial wealth.

By contrast, stock market wealth effects are largely absent. The PMG estimate for real stock price changes is 0.01 and statistically insignificant across the full sample. Interestingly, in Asia, the DPD model identifies a small but significant negative stock wealth effect (-0.02), implying that rising stock prices may not necessarily encourage consumption and could even prompt increased precautionary savings. This may be attributed to a combination of high return volatility and the concentrated nature of equity ownership. Supporting this interpretation, Singh cites Badarinza et al. (2019), noting that fewer than 10% of households in EMEs participate in equity markets, which severely limits the channel through which stock price fluctuations can influence aggregate consumption.[17]

Figure 4 given below provides further context, revealing a negative relationship between stock price volatility and domestic credit-to-GDP ratios. Countries with higher volatility—such as Turkey, Indonesia, and Peru—tend to exhibit lower financial depth, whereas more financially

[15] Abhishek Singh, "Do Housing and Stock Prices Affect Consumption in Emerging Market Economies?" *IMF Economic Review* 70, no. 3 (2022): 529–567.

[16] ibid

[17] Cristian Badarinza, Tarun Ramadorai, and Vimal Balasubramaniam, "The Household Finance Landscape in Emerging Economies," *Annual Review of Financial Economics* 11 (2019): 109–129.

developed EMEs like China and Malaysia experience lower volatility. This pattern reinforces the idea that in financially weaker markets, stock wealth is perceived as transitory and thus less likely to affect consumption.

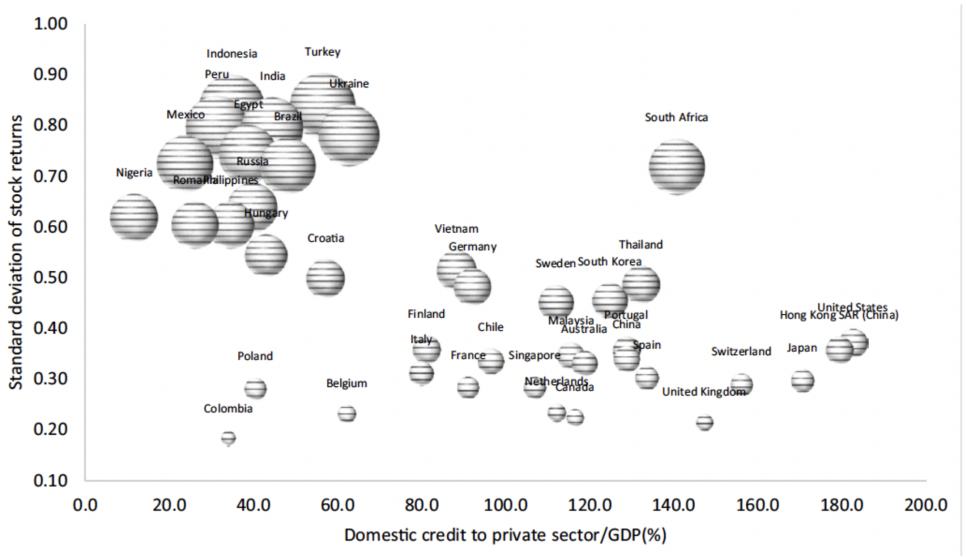


Figure 4: Relationship between Stock Price Volatility and Domestic Credit-to-GDP Ratio.

6.2 Role of Financial Deepening

To assess the moderating role of financial development, Singh analyzes a sub-sample of EMEs with above-average credit-to-GDP ratios. The findings are striking: in these financially deeper countries, the housing wealth effect increases to 0.15, and the previously insignificant stock market wealth effect becomes positive and statistically significant at 0.03. These results imply that financial development—by expanding credit access and enabling the collateralization of both stock and housing wealth—amplifies the consumption response to asset price changes. Thus, the collateral channel appears more active in financially developed EMEs, underscoring the importance of institutional and structural factors in shaping the wealth-consumption relationship.

7 Conclusion

This study set out to examine whether stock market wealth influences household consumption, drawing comparative insights from the United States and a cross-section of developing and

emerging market economies (EMEs). The evidence from the U.S. context, particularly through the work of Ludvigson and Steindel (1999), affirms that stock market wealth has a positive, albeit modest and time-varying, impact on consumption. The marginal propensity to consume out of equity wealth was found to be around 4–7 cents per dollar, with stronger effects among wealthier households who hold the majority of corporate equities. Dynamic OLS estimates confirmed a long-run relationship between stock wealth and consumption, while short-run effects appeared muted, suggesting that households respond more to perceived permanent changes in wealth than to transitory stock market fluctuations.

In contrast, findings from developing economies, particularly those presented in Singh (2022), indicate a far more limited role for stock market wealth in shaping consumption patterns. Across 20 EMEs, stock market wealth effects were weak or statistically insignificant, and in some cases even negative. Several structural constraints help explain this divergence: low household participation in equity markets, high volatility of stock returns, limited financial literacy, and shallow financial systems that constrain the use of financial wealth as collateral. However, the study also finds that in financially deeper EMEs—those with higher credit-to-GDP ratios—stock market wealth begins to exert a positive and statistically significant effect on consumption, suggesting that financial development enhances the transmission of asset wealth into consumer spending. The comparative analysis reveals that while the theoretical foundations of the wealth effect are globally applicable, their empirical strength is highly contingent on the economic environment. In the U.S., broad financial access, a culture of equity investment, and developed capital markets support a stronger link between stock wealth and consumption. In EMEs, by contrast, the stock wealth effect is largely constrained by institutional underdevelopment, though this may change as markets mature.

Overall, the results underscore the importance of context in assessing wealth effects. For policymakers in emerging markets, the findings suggest that deepening financial markets, expanding access to equity investment, and improving financial inclusion could eventually strengthen the wealth-consumption linkage, thereby enhancing the responsiveness of domestic demand to asset market dynamics. For researchers, the study highlights the need to consider heterogeneity in financial structure, asset ownership, and market access when extending consumption models

across different economies.

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