RESEARCH ARTICLES

Technology and welfare

Investigating the relationship between the ownership of technology-based assets and subjective measures of human well-being

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Abstract

The relationship between technology and individual welfare is not well understood, and as we progress into a future in which technology invades almost every aspect of life, the importance of this relationship must be recognised and an improved understanding reached. In this study, we attempt to lay a foundation for such an understanding. Using an approach based on Sen's theory of Capabilities and the South African National Income Dynamic Survey (NIDS), it estimates the effects of the ownership of technological assets on self-reported measures of well-being, both subjective and objective. Any empirical analysis of this relationship needs to control for several confounding factors. The estimation procedure employed is based on a dynamic panel approach, one that is capable of controlling for individual effects, as well as potential sources of endogeneity such as reverse causality. The results indicate that there is a statistically significant relationship between changes in the composition and value of one's technological asset portfolio and measures of social and economic well-being. Specifically, they show that increased ownership of technological assets improves one's overall life satisfaction and health status, but has little effect on one's positivity about the future. This study has found evidence that technology can improve lives when controlling for confounders such as increased wealth and status. Future work can improve upon this by better understanding the dynamics of this relationship, and disaggregating further by type of technology.

Introduction

Human well-being is a highly complex social construct, one that is based fundamentally on an intricate amalgam of factors. Unfortunately, economists have generally ignored its nuances in favour of simplified assumptions based on our modelled understanding of what is theoretically rational human behaviour. The central concept upon which much of our work is based -- utility -- has been used in an almost ignorant manner as the only real end of human pursuit. This simplified approach does not stand up to the elaborate nature of human well-being; the approach of treating well-being as an objective and definable construct is not appropriate. As elucidated above, well-being is multi-dimensional; as such, any empirical analysis will need to account for its many facets. The current analysis employs an approach first introduced by Sen (1985), which posits that the social and economic capabilities of individuals determine the extent to which they can participate in the economy, and ultimately derive welfare and utility.

This approach in itself does not incorporate multiple dimensions; however, it can be applied to a plethora of distinct situations. This idea serves as the point of departure for this study, which seeks to improve our understanding of the relationship between access to and the use of technology and one's subjective well-being.

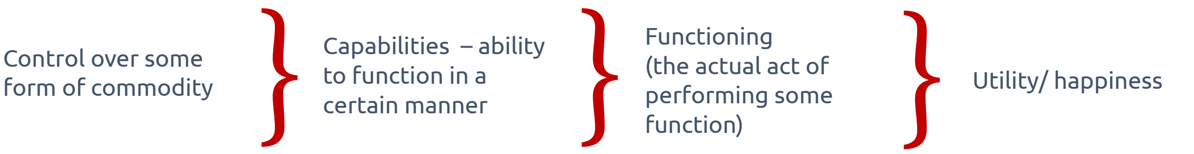
The act of empirically analysing the effect of access to and use of technology is an econometric endeavour with much promise. Moreover, combining this analytical effort with a well-defined and slightly augmented theory of human capabilities presents a productive means of bettering our understanding of human behaviour within this domain. It is here where the current study finds purpose. The capabilities approach forms the foundation of the research question which guides the current study: Does the ownership of technological assets improve subjective measures of well-being? It is here explicitly assumed that capabilities are positively correlated with subjective measures of wellbeing. Therefore, it is the purpose of the current study to derive accurate estimates for the effect of technology on the capabilities of South African individuals.

Achieving such estimates is an empirical challenge, one fraught with sources of bias and unobservable heterogeneity. There exists a number of methods that theoretically can reduce the prevalence of endogeneity in cross-sectional estimates, such as selection adjustment models, propensity score matching, and instrumental variable estimates. However, these approaches require arbitrary distributional and exclusionary assumptions which are not ideal, and that can themselves generate weak estimates if poorly specified (Casale & Posel 2011). In an attempt to overcome the shortcomings of cross-sectional estimates, the current study uses panel data and dynamic Generalised Method of Moments estimators.

The study is structured as follows. First, the theoretical framework upon which the empirical strategy is based is defined. Second, the data is introduced and described. Third, the empirical results are presented and primary findings are discussed. Finally, conclusions are provided.

Theoretical framework

As mentioned in the introduction, the foundation upon which the empirical analysis is to be applied is based on Sen's (1985) capabilities approach. This section outlines the basics of this approach in a manner that is augmented to align with the purpose of the current study. Figure 1 outlines the basic structure of Sen's original approach.



Source: Clark & Qizilbash (2005)

Figure 1: A diagram of Sen's capability approach

This diagram visually describes the interaction through which an individual has control over some scarce and economically useful commodity. This enables the individual to perform some productive function. However, one must note the necessary distinction between the ability to perform some function and the actual act of performing that function. In short, an individual must put this commodity to use and actively perform some function in order to derive utility.

Therefore, utility is an increasing function of functions, which are themselves a function of control over assets. Utility then, is indirectly an increasing function of commodities.

This study uses an augmented version of the above framework that introduces and emphasises access to and the use of technology-based assets. The concept of functioning is decomposed into a number of distinct types. Specifically, the study focuses on the effect of technology on self-reported life satisfaction, measures of individual health, employment status, and individual expectations about social status in the future. The main reason behind the need for a capabilities approach is that people are extremely heterogeous; hence, no single utility function that maps asset ownership and actions onto utility should be sufficient to model human behaviour. Moreover, there is an intuitively appealing relationship between the command over technology-based assets and the ability to benefit from the use of these assets in an economically and socially productive manner. Therefore, from both a technical and intuitive perspective, the capabilities approach is ideal. The following provides a formal description of the theoretical framework (Clark & Qizilbash 2005).

Technological assets have an instrumental value in that they enable certain functions. A function is something achievable by an individual, something an individual is capable of doing (and does do) in order to derive utility. Here, commodities refer to technological assets, and command refers to either ownership of or access to these technological assets.

First, let x_i be a vector of commodities commanded by individual i, and $g_i(x_i)$ be a mapping that converts these commodities into functions. That is, the commodities owned by individual i create some ability with which individual i uses x_i to perform some function in a manner distinct from individual . In this way, the capabilities approach allows for heterogeneity between individuals. Individuals differ in the extent to which they make productive use of commodities, certain individuals may make better use of commodities than others. Moreover, let f_i represent the utility mapping function of individual i. The use of this mapping function implies that individual i will purposefully use his or her commodities in order to reach state s_i because it results in utility. This utility function maps x_i onto s_i in the following manner:

$$s_i = f_i(g_i(x_i))$$

Where s_i refers to the vector of states that an individual can attain given his or her commodity vector. In the current study, this s_i vector can include states such as currently searching for a job, being employed, being healthy, or positive feelings about future prospects. In this same vein, examples of functions can be the ability to search for a job effectively using the internet or a wider social network enabled by ownership of a mobile phone, gaining a better understanding of health concerns via online communication, or having access to education opportunities through the use of technology. The set of capabilities available to an individual can be summarised by the following:

$$C_i = [\, s_i \mid s_i = f_i(g_i(x_i)), \quad \forall f_i \in F_i \quad \text{and} \quad x_i \in X_i \,]$$

Where C_i denotes the vector of capabilities for individual i. From the above, capabilities available to individual i are represented by all possible states, given that the states are feasible (attainable) with regard to their command over commodities. Moreover, this vector of capabilities exists for all possible utility mappings within the set of utility mappings of individual i, and all possible commodity vectors available to individual i. Put simply, we observe individual i with a specific vector of commodities (x_i), and a specific mapping (f_i) of commodities onto states s_i. However, these observable characteristics need not have been the specific ones observed: it is theoretically possible that individual i may have possessed any vector of commodities within the set X_i, and any mapping within the set F_i. Therefore, the above formulation allows for a certain level of generality. Finally, the ultimate utility that individual i derives can be represented by the function below, in which ε_i is a vector that captures all other determinants of utility not related to the capabilities of individual i.

$$U_i(C_i) = z_i(C_i, \varepsilon_i)$$

This formula is succinctly summarised in Figure 2.

Figure 2: Diagram of the theoretical framework employed in the current study

Empirical methodology and data

Identification and estimation

As mentioned in the introduction, any empirical study based on asset ownership and subjective well-being is subject to endogeneity. The main sources of this endogeneity are simultaneity and the possibility for reverse causality. That is, the exact direction of causality in not necessarily known *a priori* – Figure 3 outlines the multiple possible directions of effect.

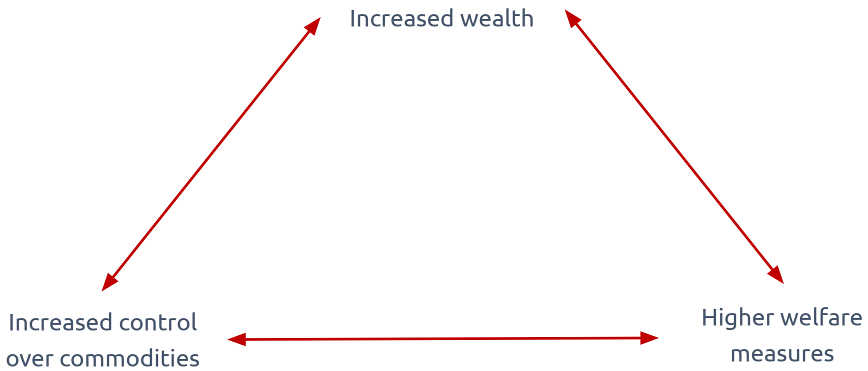


Figure 3: Diagram of the possible directions of cause and effect

The use of panel data and dynamic difference-based estimators is an explicit attempt to overcome the uncertainty of the intertemporal direction of effect. The following system of equations describes the model used in the empirical analysis:

$$\Upsilon_{it} = \vartheta\delta_{it} + \varphi_i + \varepsilon_{it}$$

$$\varepsilon it = \gamma_i + \sigma_t + \mu_{it}$$
$$i = 1, \dots, N \;\&\; t = 1, 2, 3, 4, 5.$$

Where represents the outcome variable for individual *i* at time *t*, which differs across the four distinct specifications. The study employs four distinct outcome variables, 1) satisfaction with life, 2) self-reported health, 3) employment status, and 4) future prospects. δ_{it} is a covariate matrix of control variables which are time and individual variant. φ_i captures variables that are time constant but individual variant. Moreover, the error term (ε_{it}) contains three components, one that is only time variant, one that is only individual variant, and one the is both individual and time variant.

The system is fit to the data using dynamic Arellano-Bond (Arellano & Bond, 1991) Generalised Method of Moments and fixed effects estimators. The use of Arellano-Bond estimators solves many of the problems of endogeneity mentioned earlier, specifically the problems associated with unobserved heterogeneity. However, given the dynamic nature of the estimation procedure, the use of Arellano-Bond estimators does require additional assumptions and restrictions (Kiviet, 1995); specifically, it is necessary to apply intertemporal restrictions. First, in order to account for the persistence in subjective opinion, the covariate matrix (δ_{it}) is adjusted to incorporate an AR(1) term with the following form:

$$\delta_{it} = Y_{it-1} + \theta_{it}$$

Moreover, the addition of this one period dynamic term ensures that the time series of the outcome variables are assumed to follow a Markov process.

$$E[\, Y_{it} \mid Y_{it-1} \,] = E[\, Y_{it} \mid Y_{it-s} \,] \;\forall\; s > 1$$

The Markov assumption states that the entire history of the outcome variable is contained within the most recent lagged observation. Therefore, controlling for only a single lag is sufficient to control for all historical unobservable information contained within the time series of the outcome variable. While this specification is vulnerable to scrutiny, it greatly simplifies the estimation procedure. In addition to Arellano-Bond estimators, fixed effects methods are employed. While Arellano-Bond is preferred, the value of adding fixed effects is twofold. First, it serves to test the robustness of the model specification, and second, it can be interpreted without considering the dynamic nature of the variables. That is, Arellano-Bond is specifically suited for use when dynamic interactions and persistence exist between the included variables. Therefore, the addition of fixed effects estimation allows for an alternative perspective when interpreting the results. However, it must be noted that due to the small number of time observations, the fixed effects estimation procedure cannot rely on its asymptotic properties and will likely deliver attenuated coefficient estimates. The following equation (Nickel 1981) demonstrates the nature of this inconsistency, which grows as *T* gets small.

$$\underset{n\to\infty}{\text{Plim}}\, \hat{\beta} - \beta = \frac{-(1+\beta)}{T}\,(\varphi)$$

The variable of interest is an index of technological assets owned by the individual. The index is created using a Principle Component Analysis (PCA). PCA is a valuable technique in that it allows for dramatic reduction in dimensionality while retaining the underlying global correlation structure of the data. In short, it enables the use of fewer variables while keeping the bulk of the important information contained within those variables (Wold, Esbensen & Geladi, 1987). The adequacy of each component is tested using the Kaiser-Meyer-Olkin (KMO) test (Cerny & Kaiser, 1977). Only components with a KMO value greater than 0.8 are used in the empirical analysis. Moreover, for the purpose of between group comparisons, a supervised machine learning algorithm is applied to the technological asset index. The algorithm (k-means clustering) separates the sample into four independent groups based on similarity with regard to the measure and composition of their asset vectors.

Table 1: Individual variable weighting within the Principal Component Analysis

Variable	Comp1	Comp2
TV	0.3793	-0.3496
Satellite	0.3445	0.3657
Computer	0.2805	0.5066
Cell phone	0.2175	-0.356
Electric Stove	0.3701	-0.3609
Microwave	0.4096	0.1652
Fridge	0.4086	-0.2935
Washing Machine	0.3738	0.342

Data

The empirical analysis uses data from all five waves of the National Income Dynamics Survey (NIDS). By design, NIDS is a nationally representative panel dataset which tracks the same individuals across time. The period covered by the survey is 2008-2016, and surveys were completed every two years. The entire sample is used, thus rendering the panel unbalanced. The final models are fitted to a sample size of slightly less than 13 000 individuals. Table 2 summarises the mean value of certain variables of interest across four distinct wealth groups – with each quartile representing a portion of the total population ordered from 1 to 4 by technological asset ownership. Group 1 is the poorest, and group 4 the wealthiest.

Table 2: Comparative T-tests over the means of certain variables of interest

	1	2	3	4
Health	2,14	2,07*	2,05*	2,004*
	(0,005)	(0,004)	(0,004)	(0,006)
Satisfaction	4,52	4,93*	6,35*	5,57*
	(0,15)	(0,01)	(0,014)	(0,017)
Perceived Social Rank	2,11	2,32*	2,67*	3,198*
	(0,005)	(0,005)	(0,005)	(0,007)
Social Rank Prospects	3,767	4,03*	4,35*	4,73*
	(0,009)	(0,008)	(0,007)	(0,009)
Household Size	6,03	6,15*	5,92*	5,16*
	(0,02)	(0,015)	(0,014)	(0,016)
Male	0,44	0,44	0,44	0,45*
	(0,002)	(0,002)	(0,002)	(0,003)
Food Expenditure	986,13	1160,1*	1522,66*	2471,43*
	(3,15)	(3,33)	(5,57)	(13,89)

	1	2	3	4
Education	5,03	5,89*	6,81*	8,34*
	(0.02)	(0,02)	(0,021)	(0,03)

Own calculations using the NIDS data set. Values are averages across the 5 waves. * indicates a significant difference in means at the 5% level. Each column represents a distinct quartile based on the technological asset index. With the asset index score increasing from quartile 1 to 4. Standard errors in brackets.

Table 2 confirms that ownership of technological assets differ significantly between the groups. Self-reported variables such as satisfaction and perceived social rank are higher among groups with more command over technological assets. However, these values must be interpreted with the understanding that individuals with more command over technological assets are generally wealthier, and these findings should then be expected. Essentially, the asset index is a proxy for overall wealth in most cases. Perceived health status displays an interesting result in that it is higher among individuals with fewer assets. A possible explanation for this is that any measure of perceived health is based almost entirely on a comparison with one's peers. In poor communities, in which severe illness does exist (tuberculosis for example), individuals may perceive themselves as being relatively healthy if they are free from any such disease.

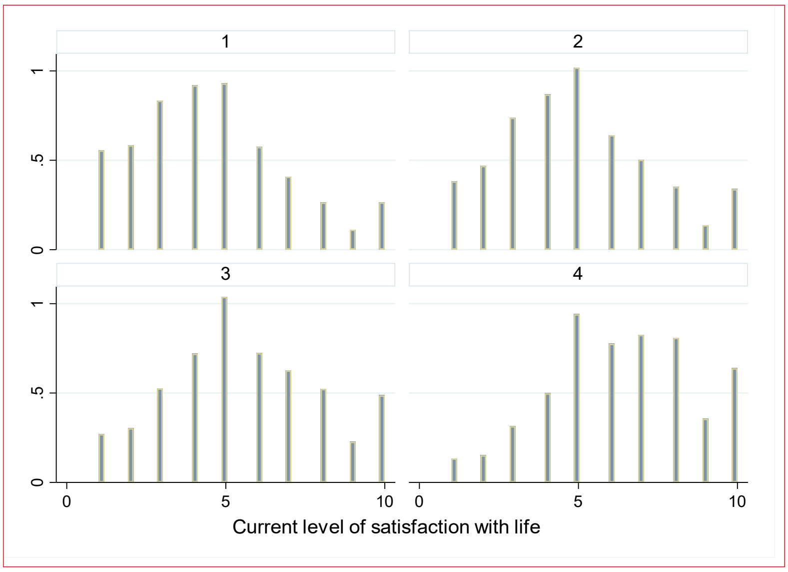


Figure 4: Histogram of satisfaction measure across quartiles

Figure 4 shows that the distribution of the measure of satisfaction varies dramatically between individuals from different quartiles. The group in quartile 1 has a distribution with a relatively long upper tail, indicating that the majority of individuals within this group report low levels of satisfaction with life. This is in stark contrast with quartile 4, a group from which the distribution indicates a large proportion that report being relatively highly satisfied with life. Figure 5 shows the distribution across the quartile groups for a self-reported measure of the individual's perceived social ranking five years from now. This is essentially a measure of how positive individuals are about their future prospects. It is clear that the distribution for the first three quartiles is relatively constant (and normally distributed); while the mean progressively shifts to the right, the margin of this shift is virtually negligible. The distribution for the group in quartile 4 is skewed to the left, with the majority of individuals reporting positive sentiment about their future prospects. This indicates that those with more technological assets are more positive about their future.

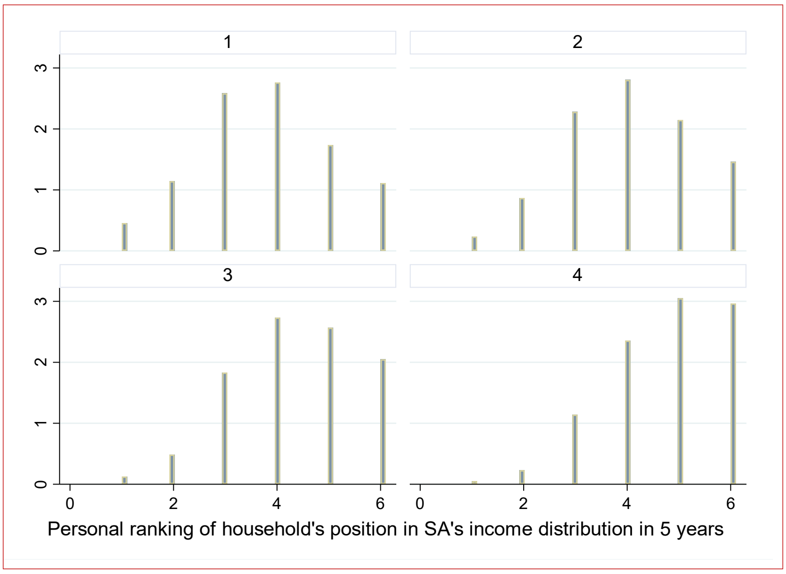


Figure 5: Histogram of future prospects across quartiles

Empirical results

Table 3: Regression results for one-step GMM and fixed effects estimators

	(1)	(2)	(3)	(4)	(5)	(6)
	Satisfaction		Future Prospects		Health Status	
	Arellano-Bond	Fixed Effects	Arellano-Bond	Fixed Effects	Arellano-Bond	Fixed Effects
Lag Outcome	-0.090*		-0.073**		-0.313***	
	(0.051)		(0.031)		(0.074)	
Tech PC1	0.163***	0.078***	0.074**	0.016	-0.012	-0.001
	(0.056)	(0.022)	(0.029)	(0.011)	(0.021)	(0.009)
Tech PC2	0.177	0.004	0.048	-0.004	-0.272***	-0.034***
	(0.207)	(0.025)	(0.101)	(0.012)	(0.086)	(0.010)
Social ranking	0.469***	0.470***	0.642***	0.627***	-0.032*	-0.007
	(0.058)	(0.025)	(0.032)	(0.012)	(0.019)	(0.010)
Health status	0.138**	0.109***	0.035	-0.055***		
	(0.054)	(0.023)	(0.027)	(0.011)		
Hours Worked	0.012**	0.013***	0.004	0.002**	0.001	-0.001
	(0.005)	(0.002)	(0.003)	(0.001)	(0.002)	(0.001)
Crime	-0.075**	-0.042***	-0.010	-0.009	-0.020	-0.026***
	(0.036)	(0.016)	(0.019)	(0.008)	(0.013)	(0.007)
Age	0.059**	0.020***	0.033***	0.015***	-0.034***	-0.017***
	(0.024)	(0.008)	(0.012)	(0.004)	(0.010)	(0.003)
Controls	y	y	y	y	y	y
Observations	5,62	23,83	4,108	21,807	6,336	24,054
Number of pid	3,448	12,917	2,68	12,336	3,879	12,993

The regressions above are estimated using Arellano-Bond and Fixed Effects estimators. Arellano-Bond is performed using Stata's xtabond command. Each regression is estimated using heteroscedastic robust standard errors. The GMM estimates are performed using a one-step procedure. Heteroscedasticity robust standard errors are included in brackets. Control variables used: Household size, marital status, education level, car ownership, medical aid (model 5& 6), and Income.

Model 1 suggests that commodities do increase the self-reported level of satisfaction of individuals over time by a statistically significant margin. This finding is corroborated by the fixed effects estimator. However, the second principle component of the commodity index is insignificant. The composition of the second component is heavily weighted toward higher value assets such as computers, washing machines and satellite dish systems. Therefore, it appears that at the upper end of the asset distribution, the marginal returns to satisfaction are greatly diminished, and insignificant. Perhaps an even more interesting finding from model 1 is that the past values of satisfaction are insignificantly correlated with the current level of satisfaction – past happiness does not determine future happiness. Model 3 shows a similar result to those found in model 1: more commodities are correlated with improved future prospects over time. That is, a positive shift in the command that an individual has over commodities will generally improve their thoughts about their own future prosperity; however, this coefficient is small. Again, the second component is insignificant, a finding that can be interpreted as more commodities among those that already have commodities does not have much effect on perceived future prospects. Keeping with this line of reasoning, it appears that the positive and significant coefficient attached to the first component indicates that an increase in a broad array, rather than an increase in a few specific, commodities is correlated with a more positive future outlook of individuals.

Model 5 shows that perceived health status is insignificantly correlated with the first commodity component, which indicates that a general increase in one's command over assets does not affect perceived health, controlling for other included variables. However, the second component is significantly and positively correlated with perceived health status. This finding could indicate that only the introduction of higher value commodities into one's life significantly affects perceived health – or broadly the ability to gain a better understanding of one's health relative to those around you. An additional interpretation could be that as one gains commodities of value, one's relative perceived ranking compared to those around you improves. Personal health could simply be an outcome of this general feeling of improvement relative to those in the same environment.

However, the models in Table 3 do not fully account for potential household dynamics, environmental factors, nor do the models incorporate any non-linear effects. Therefore, an additional set of regressions are estimated using the Arellano-Bond two step estimation procedure, which better accounts for heteroscedasticity in the errors. This heteroscedasticity is common when controlling for more household and environmental factors. Moreover, these regressions include a number of controls not used in the previous regression models. Non-linear effects are included in the form of interaction terms, each of which interacts the technological asset index with the lagged outcomes variable per model. The regression results for these additional models are displayed in Table 4.

The addition of the interaction term generates some interesting results across all four regressions. First, from model 7 is it evident that the most significant predictor of present employment is past employment, which is intuitively what one would expect. Technology, however, does not predict the ability of an individual to gain employment, as noted by the insignificance of the coefficient. Interestingly, the interaction term between lagged employment status and the technological asset index is significant and positive; it indicates that marginally more technology given that the individual was employed in the previous period improves the chances of being employed in the current period by 7 percent. A possible interpretation of this is that once employment is gained, the command over technology improves the ability of an individual to remain employed. It is possible that the command over technology enables an individual to better leverage their current employment, build and maintain better employment networks, or simply be a more effective and valuable employee.

Table 4: Regression results for two-step GMM estimators

	(7) Employed	(8) Satisfaction	(9) Future Prospects	(10) Health Status
Lag Outcome variable	0.286***	-0.152*	-0.056	-0.403***
	(0.039)	(0.084)	(0.039)	(0.033)
Tech PC1	0.001	0.803***	-0.172*	0.186***
	(0.009)	(0.235)	(0.100)	(0.062)
PC1 x lag Employed	0.077***			
	(0.027)			
PC1 x lag Satisfaction		-0.129***		
		(0.049)		
PC1 x lag Prospects			0.069***	
			(0.025)	
PC1 x lag Health				-0.046***
				(0.016)
Tech PC2	0.003	0.076	0.017	-0.005
	(0.005)	(0.221)	(0.019)	(0.010)
Decision Maker (Groceries)	0.038***	-0.013	0.066	-0.024
	(0.013)	(0.144)	(0.047)	(0.027)
Decision Maker (Assets)	0.078***	-0.129	0.043	-0.041
	(0.013)	(0.141)	(0.047)	(0.027)
Controls	y	y	y	y
Observations	27,358	4,541	15,285	31,269
Number of unique Individuals	13,967	2,899	9,071	15,600

The above regression models are estimated using Arellano & Bond estimation. The estimation used the two-step GMM procedure, which produces a less naïve weighting matrix that takes the residuals (and thus heteroscedasticity) of the first stage regression into account. Windmeijer corrected standard errors are included in brackets. Controls: Household size, marital status, educational attainment, car ownership, health (not model 4), crime, age, parent's education, identity of the household head, number of elders in the household, electricity connection, wages (only model 2), hours worked (model 2)

Model 8 uses satisfaction as an outcome variable. It indicates that the command over technology is a large positive and significant predictor of self-perceived satisfaction – almost an entire unit on a scale of 1 – 10. Interestingly, the lagged value of satisfaction is negatively correlated with the current value. The term that interacts the lagged value of satisfaction with the technological asset index is negative and significant. This negative coefficient is one without an intuitive explanation. As it is an interaction between two continuous variables, a purely econometric interpretation will be limited. It could be the case that the negative intertemporal correlation of satisfaction is so strong that it negates the positive effect of a greater command over technology. Alternatively, it could be the case that those with an already high command over technological assets have a greater negative intertemporal correlation of satisfaction.

Model 9 shows the results of a regression in which the outcome variable captures positive expectations of the future. It is notable that the coefficient on the technological asset index is negative, but significant at only the 10% level. However, the term that interacts lagged positive expectations and the technological asset index is both positive and significant. This result indicates that at a given level of the lagged expectations variable, marginally more technology improves the individual's expectations about the future. This finding seems intuitive, and one that is in line with the broader notion that individuals that are actively moving up social strata will gather more technological assets while simultaneously revising their expectations about their future prospects upwards. In this way, both the dynamic and contemporaneous correlation between technological assets and future prospects indicate that increased command over commodities improves one's expectations about future social rankings.

Model 10 shows the results for a regression with self-reported health status as the outcome variable. The results differ dramatically from those found in model 5. First, the first component of the technological asset index is found to be significantly positively correlated with health status while the second component is found to be insignificant. Model 10 does corroborate the findings of model 5 in that the lagged value of health status is negatively correlated with the current value. The interaction term of health status with the technological asset index is significantly negatively correlated with health status. However, the coefficient is extremely small. This finding reflects the absence of a strong interactive effect between the lagged health status of the individual in the previous period and their command over assets.

Conclusion

This analysis investigates the extent to which the ownership of technological assets can increase the economic and social welfare capabilities of South African individuals using the National Income Dynamics Survey dataset. The main research question underlying the empirical analysis is as follows: Does the ownership of technological assets improve subjective measures of well-being? The question is answered using dynamic panel estimation techniques which consider the intertemporal persistence that is likely to exist within the self-reported outcome variables of perceived health status, satisfaction with life, expectations about future economic ranking within society, and the objective measure of employment status.

The study makes use of Sen's (1985) capabilities approach, and posits that increased command over technological assets will increase the capabilities of an individual. That is, more access to technology will increase the ability with which individuals can perform tasks with the explicit intention of increasing their welfare. The empirical results indicate that this process is found in the data: increased command over technological assets does improve a number of self-reported measures of well-being and economic activity. More specifically, an increase in the command over technological commodities is positively correlated with employment, life satisfaction, health status, and expectations about future economic ranking within society.

These findings do seem intuitive, and would generally be in line with Sen's original writings. While the effect of technology on human life is generally positive, the complete psychological effects are not yet fully understood. The most productive outcome of this study is that there is value to be found in the use of self-reported measures, and that more work should be done to fully understand how exactly technological assets are affecting individuals in the developing world. One area where future research can improve would be from the use of a deeper analysis which accounts for different types of technology rather than relying on a single asset-based index.

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