ONLINE APPENDIX

Asymmetric Information and Remittances: Evidence from Matched Administrative Data

Thomas Joseph, Yaw Nyarko, and Shing-Yi Wang

A Theoretical Appendix

A.1 Models of Altruism

Models of altruistic remittances posit that migrants get utility from the consumption of household members at home. We present a model that adapts Lucas and Stark (1985) and Rapoport and Docquier (2006). Consider a migrant who maximizes his own utility with respect to the amount remitted:

$$u_m = u[c_m(w - r), a_h u_h(c_h)] \tag{1}$$

where the migrant's consumption, c_m, depends on w, the migrant's earnings in the host country, less r, the amount remitted to the household at home. The altruism weight attached to the household at home is given by a_h.

Consumption of the household at home is given by $c_h = c(y + r)$ where y is the earnings of household members at home. A migrant chooses a level of r to maximize his utility, and two predictions result: $\partial r/\partial w > 0$ and $\partial r/\partial y < 0$. Given our data, one testable implication of the model of altruism is that remittances should rise and fall with the earnings of the migrant.[1] Under a model of pure altruism, remittances should move with income regardless of whether income is observable by others or not.

A.2 Models of Consumption Smoothing with Altruism

Models of altruism suggest that migrants treat the consumption of household members at home similarly to their own consumption in the host country (adjusted by an altruism weight). Under the permanent income hypothesis, migrants should attempt to smooth the marginal utility of consumption over short-run fluctuations in income (Friedman 1957, Carroll 2001).[2] The key empirical predictions of this model are that consumption should respond to unpredictable income shocks but not to predictable, transitory income changes. If remittances finance consumption of households at home, altruistic migrants should smooth their remittances over anticipated fluctuations in earnings.

A.3 Exchange Motives

Exchange-based models of remittances consider remittances as a method whereby migrants pay for some type of service at home, such as taking care of the migrants' children

[1] The other interesting implication is that remittances should fall with an increase in income of the household at home, but we do not have the data to explore this.

[2] The model relies on a number of assumptions, including that credit markets work perfectly such that individuals can borrow and lend at the same interest rate and quadratic preferences. Common extensions to the standard model relax some of these assumptions to allow for a failure of the credit market and buffer stock savings (Carroll 2001). We do not consider this idea in this paper because we do not observe cash-in-hand.

or elderly parents. Similarly, an exchange-based model may be such that remittances represent a repayment for the loans used to finance the migrant's international move or the migrant's human capital investments.

We present an outline from Rapoport and Docquier (2006) of Cox's (1987) exchange motive model of remittance where migrants (and households at home) have no altruistic motives and migrants want to buy a service, X. The utility function of the migrant, denoted by m, and of the household, denoted by h, is given by $V^i(C^i, X)$ where $i = m, h$. The migrant's utility is increasing in X at a decreasing rate while the household's utility is decreasing in X at an increasing rate. The latter assumes that it is costly for the household to provide X and there is increasing disutility from this effort. For the migrant to participate in the exchange, the maximal amount that he is willing to remit, denoted by X, is such that: $V^m(I^m - R^{max}; X) = V^m(I^m; 0)$. Applying the implicit function theorem yields the result that R^{max} increases with the migrant's income. Like with the model of altruism, the exchange model predicts that remittances should increase with the migrant's income but that the observability of that income should not matter.[3]

B Data Appendix

B.1 Merging Payroll Disbursals and Remittance Transactions

We received hundreds of text files that represented two separate data sets on remittance transactions and payroll disbursals. The salary data is at the year-month level with occasional cases (fewer than 5%) in which the same individual receives multiple payments in a single calendar month. We aggregate those numbers to the total earned in that month. The remittance data is a transactions-level data set and individuals can choose to remit at any frequency that they desire. However, the fee associated with remittances is a flat rate per remittance. The mean and median number of remittances per month in the data is one. Thus, in cases where there is more than one remittance in a calendar month, we aggregate those up to the monthly level to match with the salary disbursal data. Thus, the final data set is a panel of individuals at the monthly level.

The identifiers used in the salary data set are generated by the firm and called customer registration numbers. These numbers are also available for some observations in the remittance data, and we begin by linking remittance transactions and earnings disbursals using the employee registration number. Of the observations that remain unlinked, we next use the labor card identifier, which is a government-issued identifier that is unique for every worker-contract, to match remittances and earnings. While the labor card identifer is not directly associated with earnings disbursals, we are able to link 95% of the employee registration numbers in the salary disbursal data set to an employees' data set that contains their labor card identification number as well as some characteristics of the worker, such as age, country of origin and gender.

B.2 Merging the Payroll and Remittance Data with the MOL Data

Both the MOL data on labor contracts of migrant workers and the payroll processing records contain a UAE government-issued identifier called the labor card id number. This numeric identifier is associated with each individual's contract. When workers change employer or sign a new contract with an existing employer, they receive a new labor card and a new labor card id number. We use this identifier to match the two data sets. We lose 107,698 individuals in the payroll processing data set who have missing, non-numeric or incomplete identifiers, driven by the fact that some individuals in the payroll processing data set do not provide their labor card id. Some individuals provide the company with their passport number or a driver's license, but the labor card id is

[3]The exchange model has a distinct prediction from altruism; under the exchange model, remittances can increase with the incomes of the households at home.

used in the vast majority of cases. We are able to match 553,375 individuals in the payroll processing data with their contract information in the MOL data set. There are 25,883 individuals present in the payroll processing data that are not matched into the MOL data set. This reflects the fact that some migrant workers, including domestic workers and those working in the freezone areas of the UAE, fall under the jurisdiction of the Ministry of the Interior rather than the MOL.

Appendix Table A.1: Impact of Lags and Leads of Earnings on Log Remittances

	(1)	(2)	(3)	(4)	(5)
Log(Earnings)	0.323**	0.324**	0.334**	0.339**	0.335**
	[0.005]	[0.006]	[0.005]	[0.006]	[0.007]
Lag1 Log(Earnings)	0.044**	0.046**			0.051**
	[0.004]	[0.005]			[0.005]
Lag2 Log(Earnings)		0.023**			0.028**
		[0.005]			[0.005]
Lag3 Log(Earnings)		0.004			0.009+
		[0.005]			[0.005]
Lead1 Log(Earnings)			-0.028**	-0.031**	-0.033**
			[0.004]	[0.005]	[0.006]
Lead2 Log(Earnings)				0.018**	0.023**
				[0.004]	[0.005]
Lead3 Log(Earnings)				0.007+	0.011*
				[0.004]	[0.005]
Observations	523609	428683	540938	480236	363033
Adjusted R^2	0.404	0.403	0.404	0.399	0.396

Notes: Robust standard errors clustered by individual in parentheses. +, *, ** denote significance at the 10%, 5% and 1% levels, respectively. The regressions include individual fixed effects, year fixed effects and a constant term.

Appendix Table A.2: Effects of Seasonalities on Income and Remittances

	Log Earnings		Log Remittances	
	Full Sample	All Months	Full Sample	All Months
	(1)	(2)	(3)	(4)
February	-0.015**	-0.012**	-0.007	-0.001
	[0.002]	[0.003]	[0.006]	[0.007]
March	0.006*	-0.001	0.005	0.003
	[0.003]	[0.003]	[0.006]	[0.007]
April	0.003	0.006*	-0.012+	-0.005
	[0.003]	[0.003]	[0.006]	[0.007]
May	-0.008**	-0.008*	0.014*	0.022**
	[0.003]	[0.003]	[0.006]	[0.008]
June	-0.017**	-0.018**	-0.015*	-0.006
	[0.003]	[0.003]	[0.006]	[0.008]
July	-0.002	-0.005+	-0.033**	-0.030**
	[0.003]	[0.003]	[0.006]	[0.007]
August	0.006*	0.004	-0.030**	-0.029**
	[0.003]	[0.003]	[0.006]	[0.007]
September	-0.043**	-0.040**	-0.061**	-0.059**
	[0.003]	[0.003]	[0.006]	[0.007]
October	-0.038**	-0.043**	-0.029**	-0.028**
	[0.003]	[0.003]	[0.006]	[0.007]
November	-0.016**	-0.022**	-0.022**	-0.020**
	[0.003]	[0.003]	[0.006]	[0.007]
December	0.018**	0.017**	0.003	0.007
	[0.003]	[0.003]	[0.006]	[0.007]
Observations	573132	359908	573132	359908
Adjusted R^2	0.715	0.704	0.391	0.360

Notes: Robust standard errors clustered by individual in parentheses. +, *, ** denote significance at the 10%, 5% and 1% levels, respectively. Regressions include year fixed effects, individual fixed effects and a constant term.

Appendix Table A.3: Relationship between Log Earnings and Log Remittances by Time in the UAE

	(1)	(2)
Log Earnings	0.324**	0.323**
	[0.008]	[0.005]
Log Earnings $\times$ TimeinUAE	0.000	
	[0.003]	
Log Earnings $\times$ I(Time>21 Months)		0.003**
		[0.001]
Observations	543903	543903
Adjusted R^2	0.421	0.421

Notes: Robust standard errors clustered by individual in parentheses. +, *, ** denote significance at the 10%, 5% and 1% levels, respectively. Regressions include year-month indicators, individual fixed effects and a constant term.

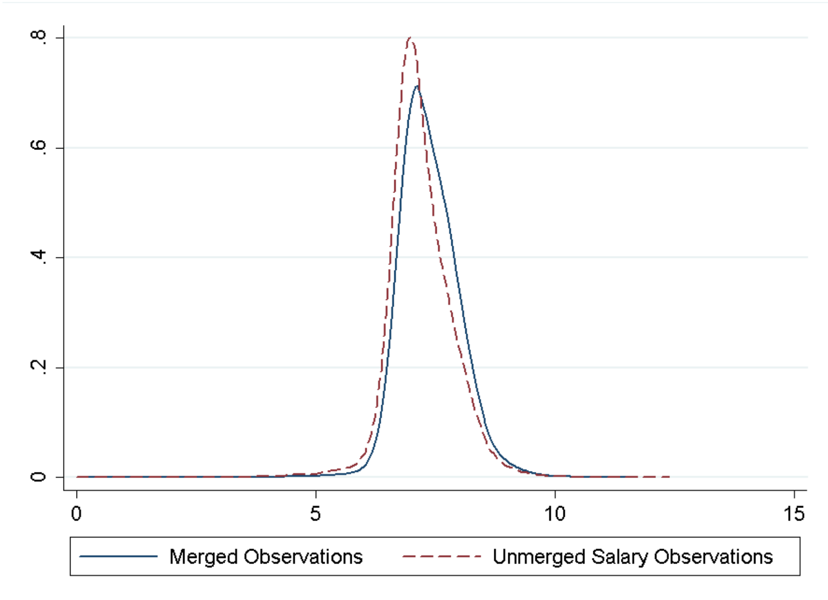
Appendix Table A.4: Home Connections and Remittance Behavior

	Ramadan	Precipitation	Extreme Rain	Temp > 100	Extreme Temp	Post Reform× Post Exp
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Impact on Log Earnings (First Stage)						
Variable	-0.015**	-0.008**	-0.028**	-0.008**	-0.004	0.077**
	[0.005]	[0.002]	[0.008]	[0.003]	[0.008]	[0.026]
Variable × I(Connections)	0.001	-0.003	0.002	0.004	-0.018+	-0.068
	[0.007]	[0.002]	[0.012]	[0.003]	[0.010]	[0.052]
Panel B: 2SLS Estimates of Log Remittances						
Log Earnings	3.600**	1.974**	1.977**	1.973**	1.977**	0.969*
	[0.819]	[0.645]	[0.689]	[0.630]	[0.704]	[0.403]
Log Earnings × I(Connections)	0.044	0.471	0.572	0.402	0.575	-0.074
	[0.032]	[0.607]	[0.825]	[0.423]	[0.558]	[0.050]
Observations	130734	128630	128630	128630	128630	7989

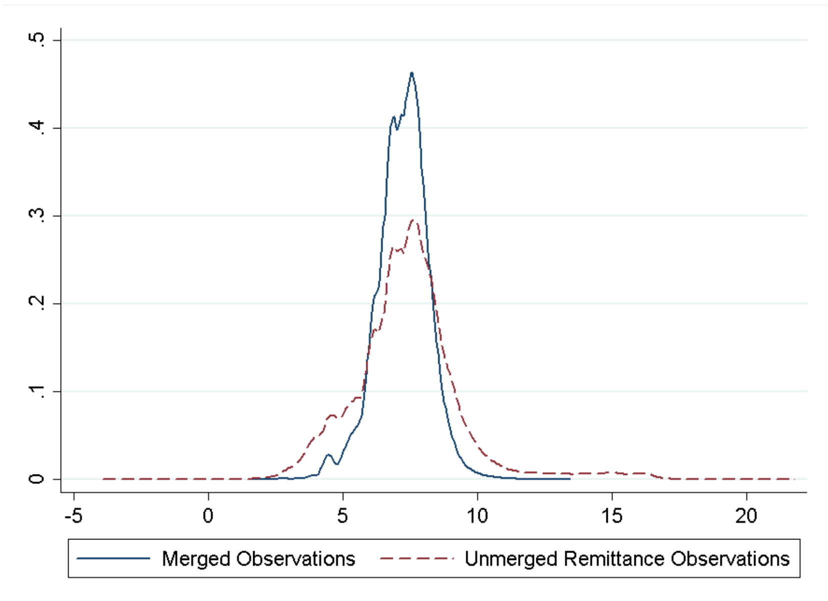
Notes: Robust standard errors clustered by individual in parentheses. +, *, ** denote significance at the 10%, 5% and 1% levels, respectively. All regressions include individual fixed effects and a constant term.

Appendix Figure A.1: Kernel Density of Log Earnings and Log Remittances

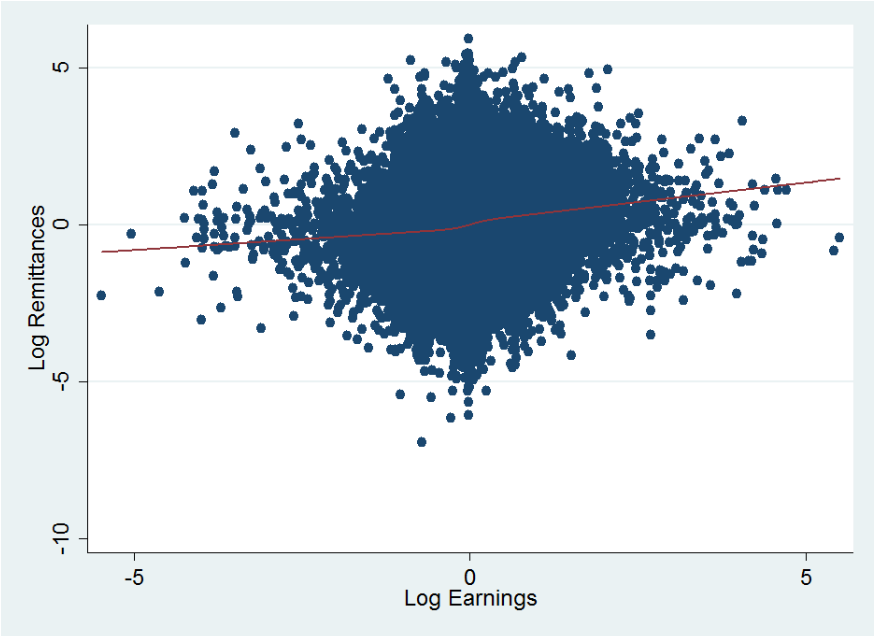
(a) Log Earnings



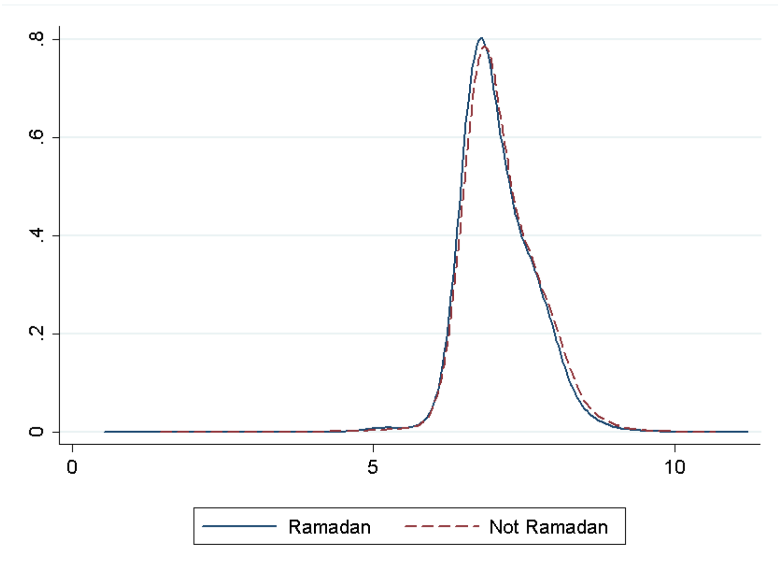
(b) Log Remittances



Appendix Figure A.2: Non-Parametric Relationship between Log Earnings and Log Remittanes



Appendix Figure A.3: Kernel Density of Log Earnings by Ramadan Months



Appendix Figure A.4: Histogram of Firms' Share of Workers with Positive Changes over Time