beliefs. To the extent there is divergence, prices diverge away from \$0.50. This relationship is more consistent with what one would expect under high risk aversion (CRRA > 1). Recall that under log utility (CRRA=1), betting functions are linear, and the equilibrium price is the mean of beliefs. In contrast, with greater risk aversion, traders respond aggressively only when prices deviate substantially from their beliefs. As such, those with extreme beliefs have the most significant effect on prices (and indeed in the limit as risk aversion approaches infinity, prediction market prices are determined by the numbers of traders who are certain that the event will occur relative to those certain it will not). These forces push prices away from mean beliefs, towards zero for longshots, and one for favorites, as seen in Figure 6.

Figure 7 formalizes this intuition. Specifically we apply our model to our empirical data on beliefs, varying parameters of the utility functions. The figure plots the implied equilibrium prediction market price against the actual mapping. From this graph, it appears that predicted prediction market prices most closely approximate actual prediction market prices for a utility function with CRRA = 5.

Our second dataset of probability beliefs that can be matched with prices comes from the Michigan Survey of Consumers, which asks respondents for the probability a \$1000 investment in a diversified stock mutual fund will increase by 10 percent or more in the next year.[13] The security corresponding to this event would be a binary equity index option with an expiry date one year from today and a strike price 10 percent above the current index level. While this exact option usually does not exist, we can estimate its price using the prices of related options.[14]

Figure 8 plots our estimated binary option price along with prediction market prices that we simulate using beliefs from the Michigan survey and different assumptions about preferences. Beliefs in the Michigan survey are quite disperse, with a mean of 31 percent and a standard deviation of 25 percent. Risk preferences therefore have a

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[13] We are grateful to Charles Manski for providing this data. The survey is described in more detail in Dominitz and Manski (2004).

[14] Specifically, we price our hypothetical binary option on each day, by interpolating an estimated implied volatility for our hypothetical option using the implied volatilities for the CBOE S&P 500 index options with the nearest strike prices and expiry dates (obtained from the *Ivy OptionMetrics* dataset). We then calculate the binary option price using the derivative of Black's (1976) pricing formula for options on futures with respect to strike price.

significant effect on our simulated prediction market price. The graph suggests that a CRRA of 1 or 2 best reconciles beliefs and binary option prices.[15]

While these results are interesting, they are obviously not a particularly robust way to measure risk aversion. Rather, we take the results as simply suggesting that models with moderate risk aversion are roughly consistent with our data on prediction market prices and the distribution of beliefs. Likewise, the model presented in Manski (2004) is at odds with these data.

5. Conclusion

An old joke about academics suggests that we are often led to ask: "We know it works in practice, but does it work in theory?" This paper arguably follows that model. In Wolfers and Zitzewitz (2004) we summarize a variety of field evidence across several domains suggesting that prediction market prices appear to be quite accurate predictors of probabilities. Hopefully this paper suggests that this evidence is easily reconcilable with theory.

All of the models we have explored yield a monotonic mapping between prediction market prices and the mean of beliefs. Moreover, we have provided several sets of sufficient conditions under which prediction market prices exactly coincide with the mean of beliefs. More generally there can be a wedge between the two, but for most practical purposes, our simulations suggest that it is likely to be small. As such, we believe that this provides a logical rationale for our earlier assertion that "markets aggregate opinions" (Leigh, Wolfers and Zitzewitz, 2003).

Manski (2004) presented a specific example "under special assumptions that may constitute a best-case scenario" in which this wedge between prices and average beliefs was large. By contrast, our analysis endogenizes the decision as to whether and how much to trade, and we find that Manski's special case is in fact a worst-case scenario. Moreover, while his worst-case scenario is at odds with observed field data, our model is consistent with observed data on the distribution of beliefs and prediction market prices.

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[15] The Michigan Survey also asks respondents for a probability that the mutual fund will increase in value in general. For this question, beliefs are distributed roughly symmetrically around 50 percent, and the binary option price we calculate is also close to 50 percent. As a result, simulated prediction market prices approximate binary option prices for a wide range of risk preferences.

Finally, we conclude with some guidance for practitioners. In most cases we find that prediction market prices aggregate beliefs very well. Thus, if traders are typically well-informed, prediction market prices will aggregate information into useful forecasts. The efficacy of these forecasts may however be undermined somewhat for prices close to \$0 or \$1, when the distribution of beliefs is either especially disperse, or when trading volumes are somehow constrained, or motivated by an unusual degree of risk-acceptance.