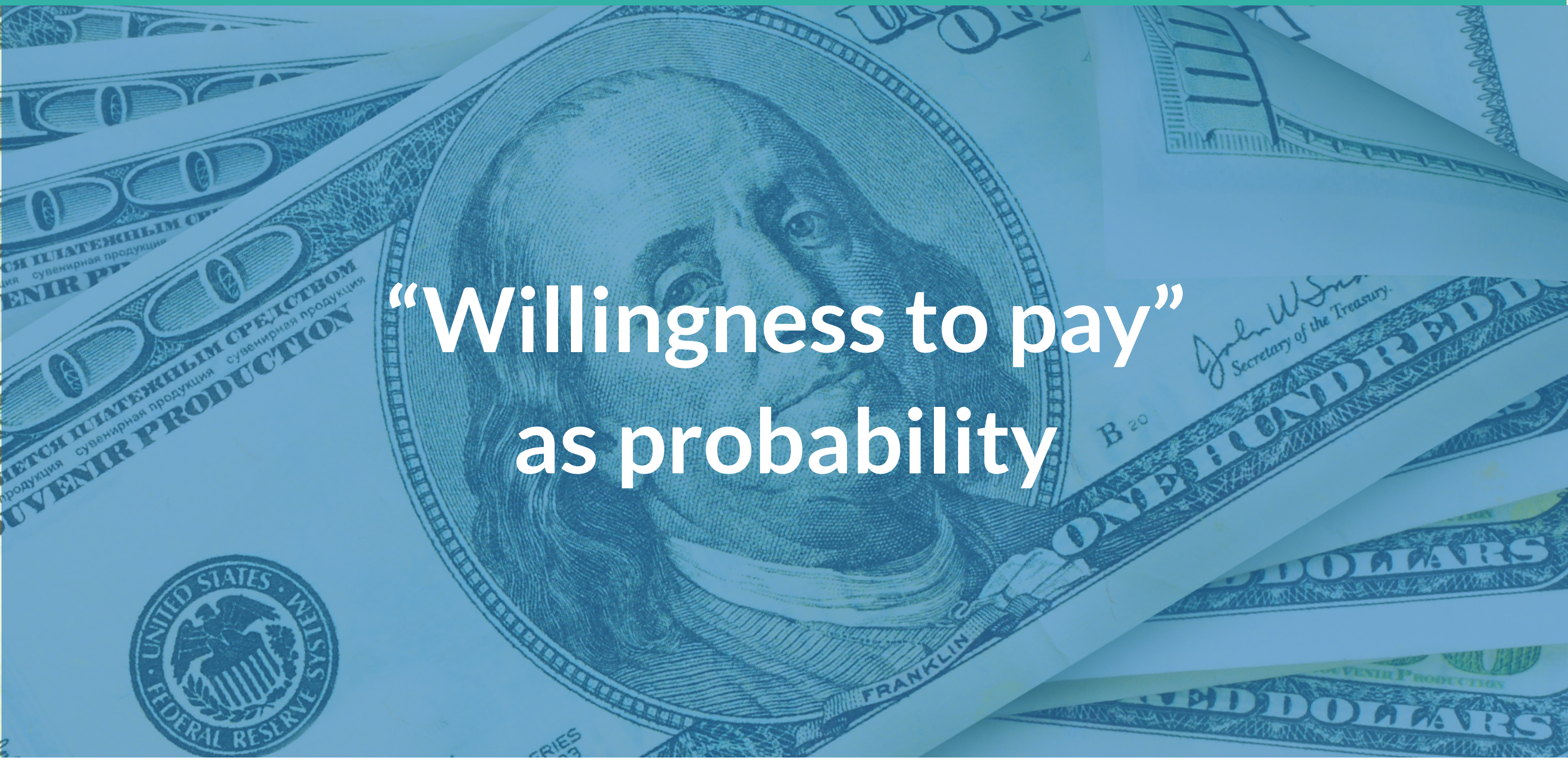

"Willingness to pay" as probability

Every purchase decision is based on the perceived value of the item in question. This perceived value fluctuates according to a wide range of factors, from competing offerings, to the trendiness of the product, to the loyalty of customers to a particular brand or outlet.

The interplay of all these factors on the item's perceived value all help shape a customer's willingness to pay.

Pricing, of course, is one of the most central factors in willingness to pay. The degree to which willingness to pay varies in response to price fluctuations is known as elasticity.

Two items with famously low elasticity are olives and anchovies – people either like them or they don't, so they either buy them or they don't. Frozen items like pizza, on the other hand, are highly price-elastic, because people stock up on them when the store offers a promotion.

One key challenge in determining the ideal price for an item is that willingness to pay is not directly observable. Retailers have historically calculated willingness to pay as a probability, using customer surveys and/or regression analysis. But these methods present significant limitations, which have now been overcome by more innovative approaches.

Traditional willingness-to-pay calculations present significant limitations

Willingness to pay is impossible to measure directly. To move the maximum number of units, the ideal price would be free. But since that's not realistic, retailers must determine a profitable ideal price through some other means.

New #AI analyses are transforming #retail #pricing, by treating many signals as factors in willingness to pay. Tweet this

To add to the complexity, humans don't make pricing decisions in absolute terms. Place a 10-euro item next to a 20-euro one, for example, and the lower price may be perceived as a better deal. In other words, context-specific information plays a significant role in willingness to pay.

Retailers have traditionally calculated an item's ideal price based on two broad types of approaches.

One approach is to make a best guess based on customer surveys. A somewhat more precise approach is to calculate willingness to pay using an elasticity formula. This formula often takes the form of a regression analysis, which calculates likely future demand based on demand in similar contexts in the past.

However, a regression analysis can only factor in a limited number of signals before it becomes noisy and unpredictable. This presents a significant limitation, because while elasticity is typically calculated as a simple volume-vs-price comparison, the real-world purchase volume of depends on a wide range of additional factors. In view of this limitation, more advanced analyses abandon the regression model altogether.

Newer probability models leave regression analysis behind.

The latest generation of probability models incorporate many factors into a continually updated probability of selling a particular item at a given price. These models can incorporate more than 200 factors, from historical demand and competing products to social media activity, and even weather.

This large number of factors enables these models to take advantage of "black box" artificial intelligence (AI) methods, which automatically pick up patterns from back-testing.

One key advantage of "seeing everything as a signal" of an item's probability of selling is that it enables retailers to make adjustments based not only on the pricing end of the elasticity curve, but also on other end: the overall volume of purchases. A high purchase volume corresponds to a higher probability of selling, which means the price may be less elastic than it appears at first glance.

In short, this form of probability analysis ties all other signals together into a single set of parameters. These parameters collectively define the limits of an item's price elasticity. What's more, this probability calculation then feeds into predictive analytics, which make dynamic pricing recommendations in response to continuously changing signals.

Thus, although this type of analysis can't directly determine a customer's willingness to pay, it provides much more fine-grained predictions. These predictions inform not only the ideal price for an item today, but also provide actionable aqinsights on the price changes that will generate optimal profits throughout an item's entire life cycle.