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Growth, Adoption, and Use of Mobile E-Commerce†

By Liran Einav, Jonathan Levin, Igor Popov, and Neel Sundaresan*

> *Mr. Spitz said he was recently stopped at a traffic light and the sun was bothering his eyes. By the time the light turned green, he had used his phone to order and pay for sunglasses.*
> (*New York Times*, June 27, 2012)

As of May 2013, 56 percent of American adults had a smartphone, and most of them used it to access the Internet. One-third of smartphone users report that their phone is the primary way they go online.[1] Just as the Internet changed retailing in the late 1990s, many argue that the transition to mobile, sometimes referred to as "Web 3.0," will have a similarly disruptive effect (Brynjolfsson et al. 2013).

In this paper, we aim to document some early effects of how mobile devices might change Internet and retail commerce. We present three main findings based on an analysis of eBay's mobile shopping application and core Internet platform.

First, and not surprisingly, the early adopters of mobile e-commerce applications appear to be people who already were relatively heavy Internet commerce users.

Second, and less obvious, adoption of the mobile shopping application is associated with both an immediate and sustained increase in total platform purchasing. The data also do not suggest that mobile application purchases are simply purchases that would have been made otherwise on the regular Internet platform.

Third, we show that while there are some differences in user behavior across the mobile applications and the regular Internet site, for instance in browsing, the differences are not yet so dramatic. We speculate that one reason may be that a significant fraction of mobile shopping is relatively nonmobile. Indeed, the use of mobile devices for e-commerce appears to be highest in the late evening!

As mentioned above, our analysis makes use of detailed data from eBay. Transactions on eBay account for a significant share of total Internet commerce in the United States, and eBay users appear to be fairly representative of the population of Internet shoppers (Einav et al. 2014). eBay is also one of the largest players in mobile commerce. According to data from comScore, eBay had over 30 million unique smartphone visitors in July 2012, second only to Amazon among retail websites.[2] For the full year of 2012, the total Gross Merchandise Volume (GMV) on eBay attributable to mobile was $13 billion, which can be compared to eBay's total GMV, which was $67.8 billion, excluding autos.[3] The specific results we report are based on detailed browsing and purchasing data for a random sample of 1 percent of all eBay users.

We organize the evidence in three sections. We first document the growth of mobile. We

* Einav: Department of Economics, Stanford University, 579 Serra Mall, Stanford, CA 94305-6072 and NBER (e-mail: leinav@stanford.edu); Levin: Department of Economics, Stanford University, 579 Serra Mall, Stanford, CA 94305-6072 and NBER (e-mail: jdlevin@stanford.edu); Popov: Department of Economics, Stanford University, 579 Serra Mall, Stanford, CA 94305-6072 (e-mail: iapopov@stanford.edu); Sundaresan: eBay Research Labs, 2065 East Hamilton Avenue, San Jose, CA 95125 (e-mail: nsundaresan@ebay.com). We thank Pat Bajari for useful comments. We appreciate support from the Alfred P. Sloan Foundation, the National Science Foundation, and the Stanford Institute for Economic Policy Research. Data access for this study was obtained under a contract between the Stanford authors (Einav, Levin, and Popov) and eBay Research Labs.

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[1] Pew Internet and American Life Project (http://pewinternet.org/Commentary/2012/February/Pew-Internet-Mobile.aspx).

[2] http://www.fiercemobilecontent.com/story/comscore-amazon-ebay-lead-all-retailers-mobile-commerce-traffic/2012-09-20.

[3] http://investor.ebayinc.com/releasedetail.cfm?ReleaseID=733959, www.dailyfinance.com/2013/01/16/ebay-inc-reports-strong-fourth-quarter-and-full-ye/.

then analyze which users were early adopters of mobile, and finally examine how mobile adoption has affected their shopping behavior. An online Appendix (available on the AER website) provides additional details about the way we construct the variables and obtain the results reported in the paper.

I. The Growth of Mobile

Throughout the paper, we focus on two types of actions to describe and measure eBay activity. We define a page download as any click or action that calls eBay servers. Such actions include entering search terms, clicking on items, placing bids, or purchasing; but they do not include scrolling down a list or clicking on a new tab within a page. A purchase is defined as a successful auction bid or a purchase of an item that was listed at a fixed price (“Buy it Now”).

We then define each activity as mobile if it was originated from the mobile-designated eBay app[lication]. So a mobile purchase is one where the shopper pressed the buy or bid button in the mobile application. In addition to smartphones and other handheld devices, the eBay app is commonly installed on tablet computers, which also are defined as mobile throughout the paper. All other activities are thus defined as nonmobile.[4]

Figure 1 presents the striking growth of eBay mobile use. From zero in 2008, mobile-originated transactions (here defined as “standard” eBay transactions via auctions or “Buy It Now” fixed prices) have been growing rapidly, increasing by a factor of ten in just a three-year period (April 2010 to April 2013). The share of mobile browsing activity—as measured by the number of page downloads—has also increased, although at a somewhat slower pace.[5]

Figure 1 also presents a similar trend in terms of users. We say that a user has adopted mobile

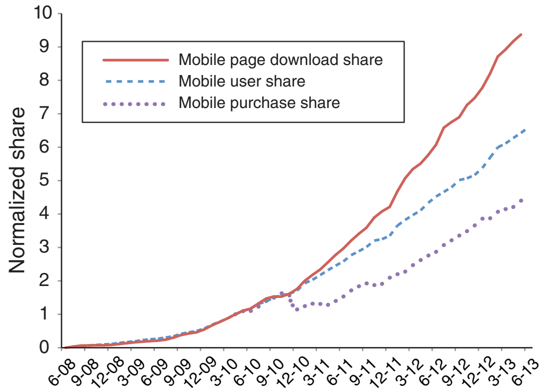

FIGURE 1. THE GROWTH OF MOBILE, 2008–2013

Notes: This figure plots three variables in a monthly time series: *mobile purchase share*, *mobile user share*, and *mobile page download share*. The mobile purchase share represents the fraction of purchases initiated using a mobile app. Monthly mobile user share is the share of all users making a purchase in a given month who had made a mobile purchase in or prior to that month. Page download share is the ratio between the number of mobile page downloads and the total number of eBay page downloads. Each time series is normalized by its April 2010 level (the first month for which we have reliable mobile page download data).

when he makes his first mobile purchase.[6] By June 2013, more than one-third of eBay’s active users (in a given month) were mobile adopters. Moreover, the monthly adoption rate (the number of new adopters in a month over the number of users yet to adopt) had increased to over 7 percent in early 2013.

II. Who are the Early Adopters?

For the most part, the early mobile adopters (defined as before) already were highly active on eBay relative to other users. We illustrate this in Figure 2. The figure shows, quarter by quarter, the eBay activity of nonmobile users who subsequently adopted mobile in the following quarter versus users who remained nonadopters for at least one more quarter. The measure of eBay activity is (nonmobile) purchase counts for the previous 12 months.

[4] This definition of mobile does not include mobile activity that originates from a regular browser (“mobile web”), such as Safari on iPhone. However, mobile web accounts for only 1.4 percent of total eBay purchases over the period we study.

[5] Initially, the number of page downloads per browsing session was 30 percent higher on mobile, given the different design of the eBay app interface. By 2013, however, the number of page downloads per browsing session was similar across mobile and nonmobile sessions.

[6] An alternative would be to define mobile adoption after the first mobile browsing session. This would almost double our measure of mobile users, but then would mean that only half the mobile user group had actually engaged in a mobile transaction.

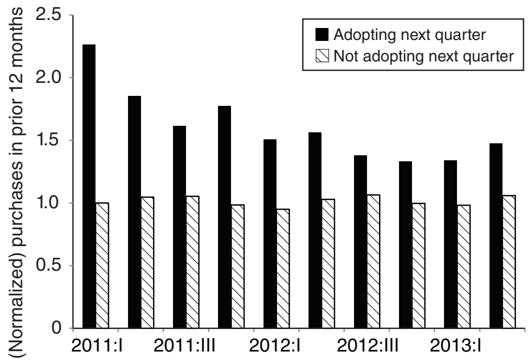

Figure 2. Mobile Adopters versus Nonadopters

Notes: This figure explores how mobile adopters differ from nonadopters in their core site usage. We define mobile adoption as a user's first mobile purchase. For each quarter, we divide all active users who have never purchased anything through a mobile application into two groups. The first group consists of those users who will make their first mobile purchase in the following quarter. The second group consists of users who will not adopt next quarter. For each group of users, we plot the mean number of purchases over the prior year, normalized by the mean of 2010 purchases for 2011:I nonadopters who did not make a mobile purchase in 2011:II.

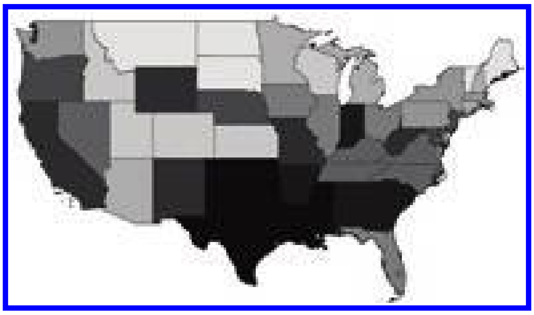

Figure 3. Geographic Intensity of Mobile Use

Notes: Figure depicts a heat map of mobile Gross Merchandising Volume (GMV) share by state, in 2012. GMV is the total dollar value of all transactions on eBay's US site. Mobile GMV share is simply that fraction of this value derived from mobile purchases. We rank states by mobile GMV share and assign each decile of the data a color, with darker colors representing higher mobile share.

The mobile adopters are, on average, heavier users than the nonadopters, with the difference being most pronounced for the earliest mobile adopters.

There is also interesting geographic variation in mobile adoption. For all users, we obtain a location measure using the primary IP address from which they log in. Figure 3 presents the mobile share of GMV for each US state during 2012. Interestingly, the states with the highest GMV share of mobile are in the south: Mississippi (22 percent); Louisiana (20 percent); Oklahoma (17 percent); and Texas (16 percent).[7]

We should note that the variation across states partly reflects variation in the smartphones and wireless infrastructure, or in the quality of broadband connections. Indeed, once normalized by the number of cell phone users who are subscribed to a data plan in each state as of the end of 2011,[8] the North-South mobile use pattern is not as sharp.

III. Effects of Mobile Adoption

Perhaps the most interesting question is how mobile adoption affects e-commerce shopping behavior. Isolating this treatment effect is a more challenging exercise given that—as we have seen in the last section—adopters and nonadopters are not fully comparable in terms of their overall eBay activity.

One way to address this selection concern is avoid comparisons across users, and instead focus on the changes in activity for the same user, before and after his adoption of mobile.

Figure 4 presents this analysis by reporting users' activity in the six months before and six months after mobile adoption, pooling all users who adopted mobile at some point during the year 2012.

The before-and-after comparison suggests that mobile adoption coincides with a large spike in activity during the month of adoption, and a subsequent permanent increase in eBay activity

[7] The lowest states in terms of mobile share are: North Dakota (6 percent); South Dakota (7 percent); Vermont (7 percent); Montana (8 percent); and Maine (9 percent). In the online Appendix, we show that some states where one might have expected high adoption, such as California and Massachusetts, were leaders at the beginning of the sample period.

[8] FCC's Sixteenth Mobile Wireless Competition Report.

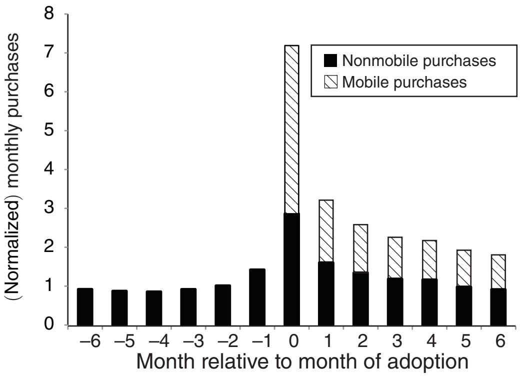

Figure 4. Effect of Mobile Adoption

Notes: Figure plots the mean (normalized) monthly number of purchases for the six months before and six months after the month of mobile adoption (month 0). Adoption is again defined by the month in which a user first makes a mobile purchase. The data consist of all 2012 adopters in our sample that first browsed eBay at least six months before mobile adoption. We calculate mean purchases for each adoption month separately and construct the average over months relative to adoption, weighted by the number of adopters in each month. Thus, the −6 value is averaged over July 2011 purchases of January 2012 adopters, August 2011 purchases of February 2012 adopters, and so on. We then normalized the monthly number of purchases so that the height of the −6 to −1 bars average to 1.

relative to the pre-adoption level. In addition, it suggests that mobile use is incremental, in that there is very little decrease in nonmobile use.

To convey a sense of the magnitude, Figure 4 shows that six months after the adoption of mobile the average number of nonmobile purchases remains virtually the same to its pre-adoption rate, but overall purchasing doubles (on average) as a result of incremental purchasing activity via the mobile app.

Even though the before-and-after analysis compares activity "within an individual," one might be concerned that the timing of mobile adoption is not random, but rather coincides with an increased interest in Internet or eBay shopping.[9] If so, comparing before adoption purchase rate to after-adoption purchasing might reflect the underlying increase in interest rather than an increase in activity that is caused by mobile adoption. Indeed, as we report in more detail in the online Appendix, this pattern of eBay use appears very similar for other eBay users who exhibit sharp (nonmobile) spikes in their eBay activity: their subsequent, post-spike activity declines but remains greater than a year earlier.

We thus conclude that mobile adoption appears to be associated with a very large transitory spike in eBay purchases, and with a smaller (but still large) sustained increase. While it is difficult to rule out the possibility that mobile adopters might have increased their purchasing in any event during the same time window, the data patterns are consistent with the view that consumers are shifting from offline to online shopping and the growth in mobile purchases is part of this general shift.

IV. The Nature of Mobile Use

So far we have focused on the effect of adoption on the level of activity on the platform, measured by transaction volume (purchases). Other activity metrics, such as page downloads, reveal similar patterns. As a final exercise, we also examine whether other patterns of activity are affected by mobile adoption.

One way to do so is by focusing on the time of the day and day of the week in which the activity tends to take place. Figure 5 presents some results regarding this aspect, by showing the distribution of mobile versus nonmobile purchasing activity over the hours of the [week]day (panel A of Figure 5) and the days of the week (panel B of Figure 5).

The clear observation from the data is that, unlike some preliminary predictions that mobile use will be different as it allows users to access the Internet in times when they would otherwise find it difficult to obtain Internet access, the time signature of mobile activity appears quite similar to that of the nonmobile one. In fact, if anything, mobile activity (relative to nonmobile one) is somewhat lower during working hours and weekdays, and slightly higher at night and over the weekend.

Figure 6 presents another way to examine the nature of mobile use by plotting the mobile share in each of the largest 15 product categories against an index, which is based on our earlier work (Einav et al. 2013a), that attempts to

[9] See also Lewis, Rao, and Reiley (2011), who illustrate a similar type of "activity bias" in a related context.

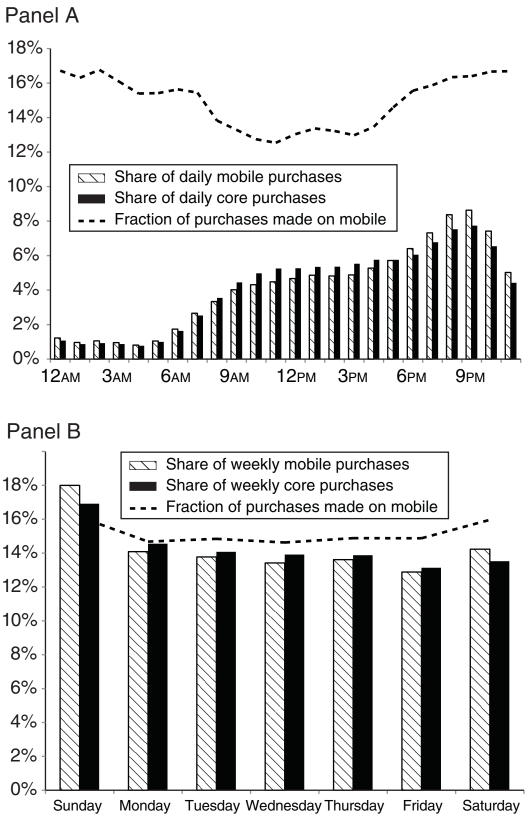

Figure 5. Timing of Use Patterns

Notes: Panel A shows the distribution of core and mobile purchases by hour of day (buyer's local time) for weekdays in 2012. Share of daily mobile (core) purchases represents the fraction of daily mobile (core) purchases made in each hour. The dashed line represents the share of total purchases in each hour initiated on mobile. For auction bids, we use the timestamp of the winning bid rather than the auction's end. Panel B repeats the same exercise for days of the week. Focusing on page downloads instead of purchases yields nearly identical patterns.

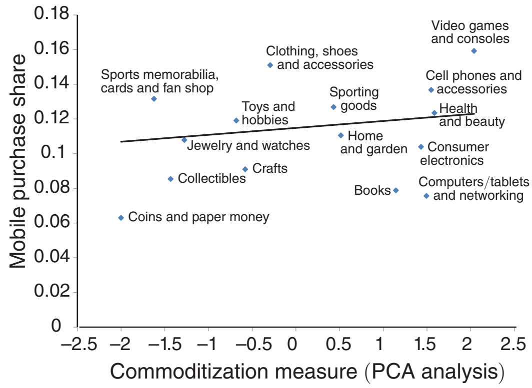

Figure 6. Mobile Penetration by Item Category

Notes: Figure presents the purchase share of mobile in each of the 15 largest product categories (as classified by eBay) against an index developed in Einav et al. (2013a), which classifies categories to more commodities (higher index) versus more unique items (lower index). The index is the result of a principal component analysis, which takes as input five category-specific statistics: the share of items with the word "new" in the title; the share of duplicate listings (Einav et al. 2013b); the share of multi-unit listings; the share of items that have eBay's product identification number; and the share of products sold by sellers who had more than a single listing. The regression line is weighted by 2012 sales volume for each category.

approximate the extent to which products in the category are commodities (higher index) versus unique (lower index).

Our hypothesis is that mobile devices, with small screens, may be easier to use to shop for commodity items, as opposed to idiosyncratic items that require more careful inspection. The figure suggests that mobile penetration is, indeed, slightly skewed toward commoditized categories, but not by much.

Finally, other aspects of mobile use also reveal that it is similar in many ways to that of non-mobile. eBay markets Daily Deals to consumers, and the share of Daily Deal purchases out of total purchases is similar (0.6 percent for mobile versus 0.5 percent for nonmobile). The distribution of transacted prices is essentially identical across mobile and nonmobile use, and transactions of highly expensive items are just as common on mobile.[10]

The one exception where mobile use is quite different is that it seems to be more often used strictly for browsing (although browsing might facilitate subsequent transactions on the core site). For example, on the core site 2.2 percent of item views result in a purchase, while on mobile the purchase rate is less than 1 percent.[11]

[10] For example, in August 2012, a convertible Chevrolet Camaro was purchased for a fixed price of $55,000 using eBay's mobile app.

[11] See also Ghose, Goldfarb, and Han (2012) for evidence on how mobile browsing differs from regular Internet browsing. Their study uses data from a South Korean microblogging website.

V. Concluding Thoughts

We presented some evidence about the penetration of mobile e-commerce, the way it affects behavior, and the nature of mobile retail use on eBay. The evidence we present should be viewed as an initial pass, both because it is based on a single, albeit large, e-commerce platform, and because mobile devices are still in their early days.

Going forward, we see several important issues that mobile adoption may raise for retail commerce. One is the interaction of online and offline shopping behavior. None of the evidence we have presented indicates so far a transformative use of mobile devices in offline shopping—indeed one could read the time use statistics as suggesting that tablet devices are primarily changing home shopping behavior. Nonetheless, we expect the opportunity to search for prices and reviews, compare online and offline products, and receive targeted coupons and promotions, eventually to have a significant effect on retail commerce.

A second issue relates to innovation and competition in online commerce. Consumers using eBay on mobile devices—even if they are at home—find products through the app, rather than through general Internet search. This suggests that advertising and marketing will be different on mobile devices. So far, we do not see much in terms of different purchase behavior or responses to marketing (e.g., our Daily Deals results). But given the early stage of mobile technology, one might expect significant room for innovation in this area.

A plausible hypothesis is that the massive adoption of mobile would facilitate new technologies that would take advantage of it and eventually alter the competitive landscape. Many such technologies are already out there, but their adoption and the competitive response to it may be slower. It thus remains to be seen whether they will have the impact some think they will.

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