The Death of a Technical Skill:
Evidence from the Demise of Adobe Flash

***Preliminary and Incomplete***

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Abstract

In 2010, Steve Jobs announced that Apple would no longer support Adobe Flash, an at-the-time popular set of tools for creating Internet applications. In the years following Jobs’ announcement, the use of Flash declined precipitously. Using data from an online labor market, we study how the market for Flash skills evolved and how Flash programmers fared. The large negative shock in the demand for Flash skills led to large reductions in hours-worked, but almost no change in wages. The reason is that Flash programmers were highly elastic in their labor supply with respect to Flash. Former Flash developers quickly “moved on” to other kinds of work requiring different skills. We conducted a survey of these Flash programmers to understand their decision-making. We find that workers are sufficiently forward-looking enough about the future of technologies that a negative demand shock can quickly become a supply shock, as workers abandon a skill with little perceived future.

1 Introduction

When the demand for some skill decreases due to a technological change, workers with that skill have to make a choice. They can continue working in that skill, perhaps at a lower wage; alternatively, they can discontinue working in that skill, say by retiring, learning a new skill, or relying on some other skill they already possess. Different workers might make different choices depending on factors such as their time horizon, ability, current human capital, and so on. Workers also have to consider the collective choices of all other similarly situated workers, as these collective choices affect the relative costs and benefits of their own choice.
In this paper, we explore how workers respond to a negative shock in the demand for their skills. The skill is Adobe Flash—a once popular software platform and programming language for creating multimedia games, advertisements and applications delivered over the Internet. It is widely believed that the cause of Flash’s demise was not technological obsolescence, but rather a business decision by Apple. In May 2010, Steve Jobs published an open letter “Thoughts on Flash” (TOF) which announced that Apple would no longer support Flash on iOS devices such as the iPhone, iPod, and iPad. Despite Jobs’ claims that the decision was made for technical reasons, this was viewed by many as pretext. The “real” reason was a desire for greater control over the experience on Apple devices, particularly the iPhone. Apple’s announcement was an effective—albeit somewhat slow-acting—poison.

Using data from an online labor market, we show that by mid-2015, job openings requiring Adobe Flash had declined more than 80% from their peak, which occurred shortly after TOF-day. Using both Flash and other skills, we show that this marketplace is a good indicator of the waxing and waning of technical skills by cross-referencing job listings to question popularity on the Q&A site StackOverflow, as well as with Google trends search data.

The focus of this paper is on how the market for Flash skills changed post-TOF-day, and how Flash programmers adjusted. We do this both empirically, using rich data from the online labor market, and also through surveys of a sample of individual Flash programmers. Our survey evidence comes from the same population of Flash programmers as our empirical work.

An attractive feature of our context is that many of the complications of studying the labor market effects of technological change do not apply. Because of the online setting, geography is immaterial. Furthermore, because of the role Apple played in killing Flash, we are less concerned that our treated workers lacked the foresight to see a coming decline in demand. This is important, as we might worry that they are a bad comparison group to workers making more prudent human capital choices. Another advantage of the role played by Apple is that it makes it straightforward to pick a reasonable starting point for the demise. A key stylized fact from the technology diffusion literature is the surprising slowness of technological adoption (Hall and Khan, 2003), and so there is no sharp event that can be pointed to as the moment the future became clear.

To begin our analysis, we start at the market level. We examine the post-TOF-day trajectory of the market for Flash skills relative to other skills.
Despite a large fall off in the number of Flash job openings posted, the number of applicants per job opening remained roughly constant, contrary to a simple static supply and demand framework—there is no evidence employers were inundated with out-of-work Flash programmers. There was no reduction in the probability that Flash openings were filled, nor a reduction in the wage paid to hired Flash programmers. Employers hiring for Flash enjoyed neither more applicants to choose from, nor lower wages, conditional upon making a hire. In short, despite an enormous shift in demand, we observe only a reduction in quantity, with no reduction in price.

We then turn our attention to individual workers active in Flash at the time of TOF-day. Because of the online setting, we can identify which workers were focused on Flash, how much experience they had, and what wages they were earning at the time the fall-off in Flash demand began. To serve as a control, we construct a matched sample of programmers who were contemporaries of the Flash programmers but were not themselves focused on Flash. Because of the large number of potential “donor” workers, we obtain excellent balance on a large number of pre-TOF-day covariates when we match.

Using our matched sample, we find that Flash programmers were seemingly unaffected by the demise of Flash on a host of outcome measures. We find no evidence they were more likely to exit the market, earn lower wages or work fewer hours in the post-TOF-day period. This lack of effects for Flash programmers is consistent with the market level findings of no changes in wages for Flash openings.

As our Flash sample worked just as many hours as the control, they had to move onto other technologies, as the amount of Flash work dried up. As we have each worker’s entire job application history, we can observe which new areas they shifted their focus to. We find that Flash developers moved into other programming technologies. For example, they moved strongly into asp.net and c#, two programming languages/frameworks. Without any additional context, we have little sense of why these technologies were common replacements. However, these are the kinds of questions our survey work is intended to address.

Our survey evidence from Flash programmers adds nuance to this adjustment story. For example, our finding that Flash workers increased their use of asp.net and c# was not a story of acquiring new skills, but rather one of relying on skills they already possessed. Many Flash programmers reported already knowing asp.net and c# when Flash began to decline.

Moving from this small puzzle, the survey offers insight into how Flash pro-
grammers thought about their careers and human capital acquisition. First, Flash developers claim to have quickly perceived Flash’s dim future, and the implication was that they needed to move on to using other skills. Interestingly, the most commonly reported way to learn was to try to get work in some new skill—to “earn while you learn.” Interestingly, this view of human capital might explain why workers moved on so quickly from Flash: when it was perceived as having no future, workers were no longer compensated by capital deepening, as the expected future payoff from Flash human capital was greatly diminished. This is in turn provides a micro-foundation for why there was so little reduction in Flash wages at the market level—the negative demand shock is also a negative supply shock.

In terms of what skill to move to post-Flash, workers reported being very aware of the risk of picking the wrong skill to specialize in. They report learning about new skills primarily from other programmers and trusted technical blogs and industry leaders. Many looked to large technology companies for signs that a new technology is likely to become a standard and hence guarantee future-proof demand for the skill. Many Flash programmers discussed the importance of focusing more on “fundamentals,” such as the design of algorithms, data structures, good development practices and so on, rather than the syntax of a particular language. These more general skills, or skills that apply in many domains, are a kind of human capital more resilient to technological change.

Our paper makes contributions to two streams of literature. This is the first paper we are aware of that makes use of longitudinal fine-grained wage, hours, and earnings data to show who switches to a new technology and who stays. They key finding of the paper is that at least in this occupational category, workers are elastic, seemingly able to switch to other skills with ease. They are also highly cognizant of changes in the market and actively follow technology trends to make their human capital decisions. This topic has received theoretical attention (Chari and Hopenhayn, 1991; Jovanovic and Nyarko, 1994; Acemoglu, 1998) but little empirical analysis. At a qualitative level, management scholars have examined how freelance workers balance learning new, emerging skills against working on projects with older skills (O’Mahony and Bechky, 2006). Recent work has also begun to consider the role of IT-enabled on-the-job learning on wages in the broader workforce (Bessen, 2016) as well as in the IT workforce (Tambe et al., 2017). Our paper examines how this learning, related to IT investment, factors into labor market dynamics. Our paper also contributes to the literature on IT labor markets. That literature has so far mostly focused
on institutional determinants of IT compensation (Ang et al., 2002; Levina and Xin, 2007; Mithas and Krishnan, 2008; Joseph et al., 2012; Bapna et al., 2013). Finally, to a lesser extent, our paper contributes to a rapidly growing literature on the platform dynamics of online labor markets (Hong et al., 2015; Agrawal et al., 2016).

The paper is organized as follows. Section 2 discusses the Adobe/Apple Flash controversy, as well as the empirical context of study. Section 3 presents a conceptual framework. Section 4 analyzes the market for Flash developers and the outcomes and choices of individuals. Section 5 presents our survey evidence. Section 6 concludes.

2 Empirical context

2.1 Apple’s announcement

On April 29th, 2010, Apple’s CEO Steve Jobs published an open letter, “Thoughts on Flash,” to justify Apple’s research decision to not support Flash applications on the iPhone, iPad or iPod Touch. Immediately following the release of Jobs’ letter, the shares of Adobe fell more than 1%. Tony Bradley, of PC World, wrote:

It boils down to Apple wanting to maintain tight, proprietary control over app development for the iPhone and iPad, and not wanting to share the pie. It also seems suspicious given Apple’s foray into mobile advertising with the iAd platform competing directly with the fairly ubiquitous Flash-based ads.

In the years following Jobs’ letter, the popularity of Flash waned considerably, though the effect was not immediate nor universally anticipated: on August 26th, 2010 the Wall Street Journal touted rising demand for Flash developers—a “trend” that seems to have had no empirical basis. Today, Flash is now a moribund technology confined to a small number of niche applications.


1

2Apple’s Jobs slams Adobe’s Flash technology. While Jobs claimed that technical considerations were driving Apple’s decision-making, it was widely believed that these arguments were a pretext and that Apple wanted to kill Flash because it was unwilling to concede so much control over the user interface and device performance to third parties.

3Apple v. Adobe: Something Just Doesn’t Add Up

2.2 Human capital of Flash development

Flash applications are technically complex and are built by Flash developers. A would-be Flash programmer needs to learn the underlying programming language, ActionScript, as well as learn Adobe’s Flash authoring tools and best practices for building and debugging Flash applications. Even for programmers knowledgeable about some other programming language, this was a non-trivial investment, likely requiring months or even years of sustained effort.\footnote{There are literally thousands of books available for learning Flash, as well as courses and online tutorials.}

2.3 Online labor market

On the platform, employers post job openings to which workers (“freelancers”) can apply. The employer then screens candidates and potentially makes a hire. If a hire is made, the wage is observed, as well as the number of hours worked, if the job was an hourly job rather than a fixed price job.

Employers self-categorize their job openings depending on the nature of the work. Employer also label their job opening with up to 10 skills, which must match a curated list, or “controlled vocabulary” of skills maintained by the platform. The controlled vocabulary of skills contains several thousand distinct skills, with new skills frequently added. As would be expected given the platform’s focus on technical work, many of the skills are programming languages, tools, and software frameworks.

These skills added by an employer are used by workers to find jobs that match their skills. Would-be applicants use these listed skills—as well as the category of the job opening—to decide which jobs to apply to. Workers also list skills in their profiles. Employers can look at past jobs completed by the applicant, which are labeled with the skills selected by the original employer.

2.4 Is the platform representative of the larger IT labor market?

A natural question is how representative the platform is compared to the technology labor market more broadly. One approach to answering this question is to show how closely Google search results from some skill match what was happening on the platform. Unfortunately, doing this for Flash is challenging, particularly since Flash is the name of a popular comic book character,
contaminates the Google trends data. An alternative skill that works better is Facebook Markup Language, widely known by its acronym, FBML.

FBML was an HTML-variant promulgated by Facebook for third-parties to use when customizing their Facebook “pages.” It appeared, became popular and then was eventually replaced with a different Facebook technology. Figure 1 shows the entire “life” of FBML on the platform, with the number of openings per month plotted over time in the bottom panel. Connecting these results to the larger world of the tech industry, in the top panel, the mean relative monthly search volume on Google for “FBML” is shown. Baker and Fradkin (Forthcoming) validate the “real world” labor market information provided by Google search data. We can see that Google search volume and the the platform job postings for FBML move closely together.

Figure 2 analyzes data from Stack Overflow, a popular website through which developers post questions and answers related to different programming languages. It plots the number of questions (normalized so highest is 1) “tagged” with various skills over time. The first three panels, from the right, show the measure for the skills java, php, and css. All are moving up and to the right. In contrast, the leftmost panels, we can see a peak followed by a decline. These are for questions tagged with “flash” and “actionscript.”

3 Conceptual framework and related work

The decline in the demand for hours of Flash skills can be thought of as a shift in the demand curve. The simply static prediction is a reduction in both
Notes: This figure plots the relative number of questions, by skill, over time posted on StackOverflow. The outcome is normalized so that the highest recorded count is scaled to 1.
the quantity of hours-worked and the wage for Flash workers. Although the direction of effects is unambiguous, the magnitudes depend on the slope of the supply curve. If supply is highly inelastic, creating a nearly vertical market supply curve, the prediction is small reductions in quantity but large reductions in the wage. On the contrary, if supply is highly elastic, the prediction is large reductions in hours-worked, but little reduction in the wage.

In broad terms, we can appreciate what factors would tend to affect the elasticity of the supply curve. In a nutshell, a more elastic supply curve means that the marginal worker can do something else that pays nearly as well. This could be because some equivalently valued skill is already possessed by the worker, or can be cheaply learned. If learning new skills is costly, or it takes a large amount of time to become productive, workers should be less elastic. Workers with long time-horizons are likely to be more elastic, as they have a longer period to recoup and switching costs.

In a dynamic setting, the situation becomes more complex. If, for example, workers see a technology as dying, and have a desire to switch—and fast—what we think of as a demand shock could actually be a supply shock, as workers try to exit. Indeed, given the importance of learning-by-doing, we might see workers charge a premium for skills perceived to have little future.

The notion that human capital investments are risky is well-established. Krebs (2003) presents a model in which households choose to invest in risk-free physical capital and risky human capital. If un-insurable labor income risk decreases, households shift away from physical capital investment towards human capital investment, which in turn increases growth and welfare. They found that the foregone growth from under-investment in human capital has large effects and that government-sponsored severance payments to displaced workers increase growth and welfare, even if these payments have to be financed with distortionary income taxation. Guvenen et al. (2014) offers an equilibrium model of the decision to acquire human capital, arguing that the progressivity of the income tax system distorts the human capital decision.

There are several other studies that consider how workers adjust to negative demand shocks. Nedelkoska et al. (2015) is most closely related paper in terms of empirical approach. The treated group are workers displaced from German firms in mass-layoff and plant closings. They find that “treated” workers have a much higher probability of switching occupations. However, one important distinction in our setting is that the cause of the displacement is a industry-wide reduction in demand for a skill rather than a particular plant closing.
Much of the literature on labor demand shocks has focused on the relative demand for different skills. For example, Chin et al. (2006) examine wage effects of the steam engine on the demand for skills in the merchant shipping industry. The steam engine increased demand for engineers but had a de-skilling effect for production work. Autor et al. (2006) discusses revisionist literature on skill-biased technical change.

There has been very little empirical work on how different workers adjust. However, the notion that different workers might be more or less able to deal with changes is long established. Schultz (1975) argues that a primary value of education is the ability to deal with dis-equilibria, meaning to spot opportunities (or risks) and then adjust accordingly. In a similar line of thinking, Nelson and Phelps (1966) argue that more educated workers are quicker to adapt promising new technologies, whereas less educated workers rely on seeing what their better educated friends do.

In terms of empirics, Bartel and Lichtenberg (1987) explores the hypothesis that educated workers have a comparative advantage with respect to the adjustment to and implementation of new technologies. Doms et al. (1997) study the adoption of technology within plants the and skills of workers. Plants that use lots of new technologies have more skilled workers. But effect is not causal—plants with higher skilled workers are more likely to adopt new factory automation technologies.

Neal (1995) uses data on displaced worker surveys to show that workers receive compensation for skills that are neither completely general nor firm-specific but rather specific to their industry or line of work. Displaced workers that find new jobs in their pre-displacement industry receive wages that resemble the cross-sectional estimates of the returns to seniority In other words, they get paid for their industry seniority, not their firm seniority. This suggests that “perhaps firm-specific factors may contribute little to the observed slope of wage tenure profiles.”

4 Results

4.1 The market for Flash skills on the platform

The demise of Flash is readily apparent in the platform data. Figure 3 plots the log number of job openings posted per month for jobs that required Flash. By way of comparison, the number of job openings requiring PHP is also shown.
PHP is a popular programming server-side language for writing web applications (e.g., Facebook was originally written in PHP). There has always been more PHP job posts, when the TOF-day letter was released, about 1,000 Flash jobs were posted per month, versus nearly about 5,000 for PHP. Despite this difference in levels, demand for the two skills grew at nearly the same rate until TOF-day. Following TOF-day, Flash jobs declined, though not immediately. By January 2015, the number of jobs was down to less than 200 per month, whereas PHP was still well above 5,000.

Demand for Flash developers, as measured by monthly job openings, fell more than 80% from 2010 to 2015. Figure 4 shows indices of the number of applications per opening, fill rate and mean wage over time for Flash and PHP. The TOF-day day is indicated with a vertical blue line. The indices are demeaned to have the same value of 0 on TOF-day using pre-period data.

In the top panel, the index is the mean log applications per opening. PHP and Flash track very closely until around the start of 2012, at which point Flash openings started receiving fewer applications. It is important to note that this is in sharp contrast to naive prediction that the number of Flash developers per opening should rise. In the middle panel, mean log wages per month are shown, for job openings filled during that month. There is no strong evidence of a decline in wages. In the bottom panel, the monthly fill rate is shown. If anything, there appears to be a lower fill rate for Flash openings.

Market-level constancy in wage levels does not imply a lack of individual- or job-opening changes. For example, there could have been a compositional
Figure 4: Attributes of Flash and PHP markets over time on the platform

Notes: This plot shows the number of job openings, per month, on the platform that require either PHP or Flash.
change, with more experienced and hence more productive workers “staying” in Flash. Different kinds of job openings could have been posted.

To examine individual outcomes for Flash programmers, we: (1) identify the platform freelancers that were has previously earned some about of money by TOF-day day (2) select those with Flash earnings as the treated group and (3) select from the non-Flash pool to create a suitable matched pair control group. We then compare the post-TOF-day outcomes of the two groups.

Steps (1) and (2) are straightforward. For (3), a decision must be made about who can be in the donor pool. While we could use all the active platform freelancers, matching a developer to, say, a graphic designer, is unattractive. Ideally, a match should be a worker using a similar technology in terms of the nature of the work, cost to learning, and so on. Further, there should be enough workers in that skill that there is a large donor group to ensure reasonable matching. As a control technology, we use PHP, and so the donor group is all the platform freelancers that had some PHP earnings by TOF-day.

4.2 Identifying Flash and PHP programmers active on and prior to TOF-dayday

We selected all workers hired for a Flash or PHP job prior to TOF-day day and then summed their hours worked on the platform prior to the announcement. Table 1 shows the summary statistics for these groups. There are about three times as many PHP developers as Flash developers. This is useful, as with this larger potential donor pool, it will be easier to create a good matched sample. Although there are clear imbalances, the two samples are not radically different in terms of their attributes.

4.3 Matching and assessing balance on pre-treatment characteristics

To create a matched sample, we use the genetic algorithm matching package developed by Sekhon (2008). The advantage of this matching approach is that it attempts to match not only on sample means, but on higher order moments of the co-variates. Table 2 compares means across the treatment—which consists of all the Flash programmers—and the control, which consists of those programmers selected by the matching algorithm.
Table 1: Attributes of Flash and PHP developers on TOF-dayday

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Flash Developers</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tenure (days)</td>
<td>1,672</td>
<td>711.962</td>
<td>439.462</td>
<td>3</td>
<td>2,167</td>
</tr>
<tr>
<td>Hourly earnings</td>
<td>1,672</td>
<td>9,893.361</td>
<td>17,291.010</td>
<td>0.000</td>
<td>161,195.700</td>
</tr>
<tr>
<td>Hours worked</td>
<td>1,672</td>
<td>717.427</td>
<td>1,053.441</td>
<td>0.000</td>
<td>8,649.833</td>
</tr>
<tr>
<td>Total hours</td>
<td>1,672</td>
<td>176.823</td>
<td>561.758</td>
<td>0.167</td>
<td>8,583.333</td>
</tr>
<tr>
<td>Number of distinct employers</td>
<td>1,672</td>
<td>1.715</td>
<td>1.860</td>
<td>1</td>
<td>31</td>
</tr>
<tr>
<td>Bachelors degree?</td>
<td>1,672</td>
<td>0.446</td>
<td>0.521</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td><strong>PHP Developers</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tenure (days)</td>
<td>5,440</td>
<td>696.220</td>
<td>469.627</td>
<td>2</td>
<td>2,191</td>
</tr>
<tr>
<td>Hourly earnings</td>
<td>5,440</td>
<td>10,246.330</td>
<td>19,106.370</td>
<td>0.000</td>
<td>272,020.400</td>
</tr>
<tr>
<td>Hours worked</td>
<td>5,440</td>
<td>737.038</td>
<td>1,195.290</td>
<td>0.000</td>
<td>14,902.670</td>
</tr>
<tr>
<td>Total hours</td>
<td>5,440</td>
<td>3,199.734</td>
<td>64,473.840</td>
<td>0.167</td>
<td>2,770,701.000</td>
</tr>
<tr>
<td>Number of distinct employers</td>
<td>5,440</td>
<td>2.167</td>
<td>2.320</td>
<td>1</td>
<td>36</td>
</tr>
</tbody>
</table>

**Notes:** This table reports the attributes of PHP and Flash developers on TOF-dayday.

Table 2: Comparison of worker covariate means on TOF-day, for the matched sample, with t-statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>PHP</th>
<th>Flash</th>
<th>t-stat</th>
<th>Used in matching?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hours-worked</td>
<td>796.37</td>
<td>850.78</td>
<td>-1.08</td>
<td></td>
</tr>
<tr>
<td>Hourly earnings</td>
<td>10,562.74</td>
<td>11,728.28</td>
<td>-1.45</td>
<td></td>
</tr>
<tr>
<td>Past employers (count)</td>
<td>1.89</td>
<td>1.80</td>
<td>0.91</td>
<td>✓</td>
</tr>
<tr>
<td>Masters degree</td>
<td>0.31</td>
<td>0.30</td>
<td>0.42</td>
<td>✓</td>
</tr>
<tr>
<td>Bachelors degree</td>
<td>0.49</td>
<td>0.47</td>
<td>0.98</td>
<td>✓</td>
</tr>
<tr>
<td>HS degree</td>
<td>0.08</td>
<td>0.07</td>
<td>0.30</td>
<td></td>
</tr>
<tr>
<td>Doctoral degree</td>
<td>0.01</td>
<td>0.01</td>
<td>-0.24</td>
<td></td>
</tr>
<tr>
<td>Associates degree</td>
<td>0.17</td>
<td>0.18</td>
<td>-0.79</td>
<td>✓</td>
</tr>
<tr>
<td>Missing education recs</td>
<td>0.19</td>
<td>0.18</td>
<td>0.48</td>
<td></td>
</tr>
<tr>
<td>Fraction hours in focal skill</td>
<td>0.51</td>
<td>0.53</td>
<td>-0.13</td>
<td>✓</td>
</tr>
<tr>
<td>Avg. earnings per day</td>
<td>14.85</td>
<td>15.59</td>
<td>-0.85</td>
<td>✓</td>
</tr>
<tr>
<td>Average wage</td>
<td>12.00</td>
<td>12.44</td>
<td>-1.83</td>
<td></td>
</tr>
<tr>
<td>Log hourly earnings</td>
<td>8.14</td>
<td>8.25</td>
<td>-1.36</td>
<td>✓</td>
</tr>
<tr>
<td>Log tenure (in days)</td>
<td>6.23</td>
<td>6.28</td>
<td>-1.61</td>
<td>✓</td>
</tr>
<tr>
<td>Log average wage</td>
<td>2.39</td>
<td>2.41</td>
<td>-0.94</td>
<td>✓</td>
</tr>
<tr>
<td>Log hours-worked</td>
<td>5.75</td>
<td>5.84</td>
<td>-1.20</td>
<td></td>
</tr>
<tr>
<td>Frac. of months earned</td>
<td>0.58</td>
<td>0.60</td>
<td>-2.08</td>
<td>✓</td>
</tr>
<tr>
<td>Frac. of months active</td>
<td>0.64</td>
<td>0.67</td>
<td>-2.47</td>
<td>✓</td>
</tr>
</tbody>
</table>

**Notes:** This table reports the means for the matched sample of Flash versus PHP programmers. The t-statistic for a difference in means is reported. If that covariate or its transform was used in the matching algorithm, it is indicated as such in the far right column.
4.4 Visualizing the matched PHP/Flash sample over time

In addition to static measures, we can also examine the time series for the two groups. In Figure 5, we plot the average sample values for: (1) the log average wage, (2) log total earnings, (3) log hours-worked (4) log wage bid.

We can see that for most outcomes, the pre-period match is quite good. For no outcome do we see a difference large enough that the confidence intervals do not overlap. Note that some of these “quantity” measures, such as hours-worked and earnings will mechanically decrease after TOF-day, as workers leave the platform and so their quantities go to zero. In the post period, the two mainly overlap, with perhaps some evidence of higher wages and earnings for PHP in much later months. We will explore the post-period outcomes next.

4.5 Effects of the demise of Adobe Flash on Flash programmers

With the matched data set, the treatment effects can be estimated with a simple comparison of means. We estimate

$$y_{iT} = \beta_0 + \beta_1 \text{FLASH} + \epsilon,$$

where $y_{iT}$ is some outcome of interest, $T$ is the post-TOF day of measurement and FLASH is an indicator for that the developer was a Flash developer.

Table 3: Matching estimates of the effects of Adobe Flash decline on hours, wages and earnings

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Any hours (1)</th>
<th>Log hours (2)</th>
<th>Log mean wage (3)</th>
<th>Log earnings (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flash Workers, Trt</td>
<td>-0.001</td>
<td>-0.092</td>
<td>0.011</td>
<td>-0.089</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.089)</td>
<td>(0.024)</td>
<td>(0.095)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.990***</td>
<td>6.259***</td>
<td>2.562***</td>
<td>8.812***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.068)</td>
<td>(0.018)</td>
<td>(0.073)</td>
</tr>
<tr>
<td>Observations</td>
<td>2,086</td>
<td>2,050</td>
<td>2,050</td>
<td>2,057</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.00003</td>
<td>0.001</td>
<td>0.0001</td>
<td>0.0004</td>
</tr>
</tbody>
</table>

Notes: This table reports propensity score matching estimates for the effects of the collapse of Flash on workers in that field, using PHP-focused software developers as a control. Significance indicators: $p \leq 0.10 : \dagger$, $p \leq 0.05 : \ast$, $p \leq 0.01 : \ast\ast$ and $p \leq 0.001 : \ast\ast\ast$. 

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Figure 5: Matched sample monthly time series for Flash and PHP programmers

Notes: This figure shows the by-month outcomes for Flash programmers and their matched-sampled PHP counterparts.
Table 3, Column (1) reports a regression where the outcome is an indicator for whether the worker has worked any hours post TOF-day. In Column (2), the dependent variable is the log cumulative hours worked, by time $T$, post-TOF-day. In Column (3), the dependent variable is the log average wage. In Column (4), the dependent variable is the log cumulative earnings.

On all outcomes, there is no evidence of a large difference between the Flash group and their PHP counter-parts. All effects are essentially precisely estimated zeros.

We now turn to the same estimate, but in a panel framework with worker-specific and week-specific fixed effects:

$$y_{it} = \sum_t \beta_t (\text{FLASH}_{it} \times \text{Week}_t) + \sum_t \delta_t \text{Week}_t + \gamma_i$$  \hspace{1cm} (2)

Our interest is in the $\beta_t$ coefficients—both the pre-period, as they allow us to assess the parallel trends assumption, and in the post-period, as they measure treatment effects. Figure 6 plots the $\beta_t$ coefficients from Equation 2, for the following outcomes: (1) indicator for whether the worker was active on the platform, as measured by earning at least some amount of money, (2) their log average wage, (3) their log earnings, (4) their log hours-worked, (5) their log number of applications sent (6) their log wage bid on the sent applications.

We can some evidence that Flash developers are less likely to still be active near the end of the sample, with reductions as large as 10 percentage points. For the average wage, we can see that the confidence interval comfortably includes zero in every period, though there is perhaps some evidence of a u-shaped pattern. For example, about 2 years after TOF-day, we see average wages that are 5% lower, though by the end of the panel, there is no difference. While we lack the precision to make strong claims, this is perhaps some evidence of a decline in earnings while Flash workers are acquiring new skills. There is a similar decline in hours-worked, though it does not appear to re-bound quite as much. There is no decline in applications. For wage bids, we can see that in the pre-period, Flash workers were bidding somewhat more (about 10%) which declined and then rose later, near the end of the period.

4.6 Skill-focus of Flash programmers

As we observe all the applications sent by workers, we can observe how their job-seeking focus changed with respect to skills. We can do this by taking
Figure 6: Matched sample monthly time series for Flash and PHP programmers

Notes: The collection of $\beta_t$ coefficients from Equation 2.
all applications send by Flash and PHP developers in the sample and then calculating how many applications were sent to each skill, by group. We then compute by the by-month difference and normalize to zero in the pre-period.

Figure 7 plots the normalized difference by month for a collection of skills. The skills are ordered by the average gap between Flash and PHP in the post-period. The biggest gains are in asp.net and c#, both of which clearly began pre-TOF-day. There is also some evidence of a shift towards SQL and jQuery. Aside from these changes, there is not much evidence of a strong shift to other skills compared to the PHP developers.

5 Surveys of Flash developers

To provide some qualitative support for our interpretation of the empirical analysis, we surveyed Flash developers on the platform from which we drew our archival data.
5.1 Data Collection

The survey data were collected from developers who a) participate on the online labor platform and b) who are using Flash or have used Flash on prior projects. Survey questions were based on responses from two prior rounds of pilot surveys, which elicited free-text responses on the nature of Flash development, skill obsolescence, and the impact that changes in the Flash market had on respondents. Survey respondents were paid a fee of $10 to complete the survey. Selection of the respondents, administration of the survey, and payment were handled by a third party. The data were collected from respondents in late June and July of 2017. Of those who were invited to take the survey, 43% accepted.

5.2 Descriptive Statistics

5.2.1 Key sample characteristics

Table 4 reports some basic descriptive statistics about the developers in our sample. Most respondents deemed themselves proficient in Flash relative to others on the platform, and anticipated working on technical projects for about eighteen more years.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Years left that you will pursue technical projects</td>
<td>18.32</td>
<td>11.21</td>
<td>127</td>
</tr>
<tr>
<td>Flash Proficiency relative to other developers</td>
<td>7.88</td>
<td>1.71</td>
<td>134</td>
</tr>
</tbody>
</table>

Table notes: For proficiency, developers were asked to evaluate themselves relative to other freelancers on the site. A score of 7 would have indicated that they were more proficient than 70% of developers on the site.

Figure 8 shows changes in the time spent on a) Flash projects and b) the platform between 2010 and 2017. For Flash projects, respondents were asked to provide information about time spent as a fraction of all their time on freelance sites. For freelance platforms, they were asked to report time as a fraction of all of their working time. A score of 10 corresponds to between 71%-80% and a score of 6 corresponds to 31%-40%. The responses from the surveys indicate a significant decline in the amount of time spent on Flash projects between 2010 to 2017. However, the overall time spent on the platform slightly increased, which, when considered alongside the Flash results, is consistent with the interpretation
that workers continued to use the platform, but switched from Flash to other
technologies as Flash declined.

Figure 8: Change in time spent on Flash projects and on the online platform
between 2010 and 2017

Figure Notes: For Flash projects, respondents were asked to pro-
vide information about time spent as a fraction of all their time
on freelance sites. For freelance platforms, they were asked to re-
port time as a fraction of all of their working time. A score of 10
corresponds to between 71%-80% and a score of 6 corresponds to
31%-40%.

In Table 5, we report which other skills were most commonly held by workers
who also were familiar with Flash. Javascript and Php–another skill we focus
on in the empirical portion of this study–are two of the most popular skills held
by freelancers who also were familiar with Flash. HTML5, which was often
referred to by respondents as a skill that was replacing Flash in many areas of
web development, is also a popular choice, and may reflect the fact that some
developers transitioned from Flash to HTML5 as Flash fell out of favor.

Table 5: Other technical skills most commonly held by Flash developers

<table>
<thead>
<tr>
<th>Skill</th>
<th>Respondents with skill</th>
<th>Fraction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Javascript</td>
<td>67</td>
<td>0.22</td>
</tr>
<tr>
<td>Php</td>
<td>46</td>
<td>0.15</td>
</tr>
<tr>
<td>Html</td>
<td>35</td>
<td>0.12</td>
</tr>
<tr>
<td>Java</td>
<td>33</td>
<td>0.11</td>
</tr>
<tr>
<td>Html5</td>
<td>27</td>
<td>0.09</td>
</tr>
<tr>
<td>C#</td>
<td>26</td>
<td>0.09</td>
</tr>
<tr>
<td>Css</td>
<td>26</td>
<td>0.09</td>
</tr>
<tr>
<td>C++</td>
<td>15</td>
<td>0.05</td>
</tr>
<tr>
<td>Jquery</td>
<td>13</td>
<td>0.04</td>
</tr>
<tr>
<td>Adobe Photoshop</td>
<td>12</td>
<td>0.04</td>
</tr>
</tbody>
</table>

5.2.2 Effects of Flash decline on workers

The effects of the change in the Flash market on workers are documented in Figure 9. Survey respondents reported how they perceived that the hours and wages they spent on Flash projects changed as a result of changes in the Flash market. Their responses suggest there was a substantial decline in the time spent on Flash projects, and a somewhat smaller decline in wages. This is consistent with one of the key findings from our analysis of archival data, which is that hours were more strongly affected than wages. Overall wages and hours spent on the online platform were also negatively impacted, but to a smaller extent.

5.2.3 How did Flash developers adjust?

Table 6 reports how developers adjusted to changes in the Flash market. Although workers took different approaches, about 65% switched to other skills, with the largest fraction of workers in our sample (close to half) responded by abandoning Flash altogether and switching to other technologies.

Figure 10 reports summary statistics indicating whether respondents learned new skills or reverted to existing skills. Respondents were asked to respond to how important each strategy was ranging from 1 (not very important) to 5 (extremely important). Among the options, and consistent with the results in
Figure 9: How were you affected by changes in the market for Flash?

Table 6: Adjusting to changes in the Flash market

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Fraction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stayed with Flash</td>
<td>33</td>
<td>0.25</td>
</tr>
<tr>
<td>Mostly stayed with Flash</td>
<td>13</td>
<td>0.10</td>
</tr>
<tr>
<td>Mostly switched to other skills</td>
<td>20</td>
<td>0.15</td>
</tr>
<tr>
<td>Switched completely to other skills</td>
<td>67</td>
<td>0.50</td>
</tr>
</tbody>
</table>
Table 6, learning new skills was more common than switching to existing skills or enhancing existing skills.

Figure 10: How did you adjust?

<table>
<thead>
<tr>
<th>Method</th>
<th>1 (Not important)</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5 (Very important)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Learn new skills</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Research skills to learn</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Enhance existing skills</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Switch to existing skills</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

How did workers who switched to new technologies learn these skills? Respondents’ answers to this question are shown in Figure 11. Among the different methods they could have used to acquire this new human capital, what emerges from the survey responses is that learning on-the-job and visiting online forums (e.g. Stack Overflow) were the two most important ways respondents chose to learn new technologies. By contrast, respondents described the traditional classroom setting as being less important for learning new skills. Unpaid projects were in the middle of these in terms of importance, but later in the analysis, we show that among younger workers, it is a much more common option.

Figure 12 documents the specific factors workers pay attention to when choosing which skills to focus on. The most important of these are current demand, followed closely by future demand for the skill.

Given the importance of on-the-job learning and hands-on projects for learning these skills, we also asked developers about how the need to learn new technologies influences project choice and bidding strategies. Respondents said that they need only to be about 66% comfortable with a new technology before
beginning to work on new projects that required use of that technology. Developers, on average, also said that they tend to lower their bids by about 40% when bidding on projects for which they are using new technical skills and only expect to be about 60% of the way towards their full productivity when bidding on projects where they use new skills. The distribution of the responses on this project and bidding behavior is shown in Figure 13.

5.3 Correlations with age and focus

In this section, we analyze how the effects we observe differ by at what point the developer is in her career, or how focused the developer was on Flash before TOF-day. In Table 7, we report correlations between age and how changes in the Flash market affected wages and hours. Changes in this market appeared to affect older workers more strongly than it did younger workers. There is some, limited evidence in the next two columns that the decline in wages was more important for workers who were more focused on Flash and who logged more hours with Flash. This is consistent with what we observed in the text responses—developers stated that the demand for Flash work shifted to special-
Figure 12: Which factors influence which skills you focus on?

![Bar chart showing factors influencing skill focus]

- Current demand
- Future demand
- Market wage
- Maturity/stability
- Life span of skill
- Buzz/Word of Mouth
- Difficulty to learn

Figure 13: Respondents’ project and bidding strategies

![Bar charts showing required level of expertise and (downward) bid adjustment]

- Required level of expertise (%)
- (Downward) bid adjustment (%)

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ized projects. Many developers who completed our survey reported that hourly rates actually went up for Flash projects, but shifted towards smaller, specialist projects that were primarily completed by a limited supply of experts. Younger, generalist workers fled the Flash market, seeing a limited future in it. Older, specialized workers, however, were able to continue to earn (at potentially lower hours and higher rates) using Flash even as it continued to decline.

Table 7: Correlations among years remaining, focus, and impact

<table>
<thead>
<tr>
<th></th>
<th>Years remain</th>
<th>Proficiency</th>
<th>2010 Flash focus</th>
</tr>
</thead>
<tbody>
<tr>
<td>Effects on Flash wages</td>
<td>-0.19</td>
<td>-0.07</td>
<td>-0.03</td>
</tr>
<tr>
<td>Effects on Flash hours</td>
<td>0.04</td>
<td>0.05</td>
<td>0.05</td>
</tr>
<tr>
<td>Impact on Flash development</td>
<td>0.04</td>
<td>0.13</td>
<td>-0.05</td>
</tr>
</tbody>
</table>

The estimates in Table 8 reflect how career tenure and focus are related to developers’ adjustment strategies. The correlations are not strong. Those who were most proficient with Flash technology were most likely to switch to new skills. Developers who were less concentrated in Flash technology as a part of their portfolio (i.e. had a more balanced portfolio of skills) were more likely to switch to an existing skill.

Table 8: Correlations among years remaining, focus, and adjustment strategies

<table>
<thead>
<tr>
<th></th>
<th>Years remain</th>
<th>Proficiency</th>
<th>2010 Flash focus</th>
</tr>
</thead>
<tbody>
<tr>
<td>Switch to existing skills</td>
<td>0.09</td>
<td>0.01</td>
<td>-0.08</td>
</tr>
<tr>
<td>Enhance existing skills</td>
<td>-0.02</td>
<td>0.01</td>
<td>-0.09</td>
</tr>
<tr>
<td>Research new skills</td>
<td>-0.10</td>
<td>0.04</td>
<td>-0.13</td>
</tr>
<tr>
<td>Learn new skills</td>
<td>-0.07</td>
<td>0.14</td>
<td>-0.08</td>
</tr>
</tbody>
</table>

Table 9 shows correlations between career tenure and how workers learn new skills. Some of these correlations are strong. They indicate that younger workers are less likely to learn from books, classes, or through coworkers or friends. Instead, younger developers are more likely to learn new technologies by working on unpaid projects, perhaps through platforms such as Github7, and using online forums like Stack Overflow8 as needed. Older workers are

7http://www.github.com
8http://www.stackoverflow.com
more likely to use traditional channels like books or courses, and are more likely
to learn on-the-job through paid projects.

Table 9: Correlations among years remaining and skill acquisition channels

<table>
<thead>
<tr>
<th>Years remaining</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Books or manuals</td>
<td>-0.08</td>
</tr>
<tr>
<td>Traditional classroom env.</td>
<td>-0.20</td>
</tr>
<tr>
<td>Friends or coworkers</td>
<td>-0.17</td>
</tr>
<tr>
<td>Online courses</td>
<td>-0.23</td>
</tr>
<tr>
<td>Online forums</td>
<td>-0.05</td>
</tr>
<tr>
<td>Learning on-the-job</td>
<td>0.01</td>
</tr>
<tr>
<td>Learning by doing unpaid</td>
<td>0.20</td>
</tr>
</tbody>
</table>

5.4 Selected free text responses

We also collected free text responses to questions related to the market for
Flash and how workers felt they were affected. These responses are useful for
providing qualitative support for the key arguments we try to advance in the
paper.

Describe any changes you have noticed in the market for Adobe Flash
projects between 2010 and 2017 - either the numbers of jobs posted,
the offer rate, or types of projects. If you began working with Adobe
Flash after 2010, describe any changes you have seen in the market
since you joined.

“The number of available jobs is far fewer in 2017 than in 2010. The
types of Flash projects I get are more interesting and difficult
than I used to, which may be in part because I have more experience,
but may also be because the available jobs in ActionScript are highly
specialist, as the more general usage of Flash has shifted to HTML5.”

“Work in Adobe Flash has been drastically decreased in 2017 as com-
pared to 2010. People are more interested in other languages due to
the reason that Flash is not supported by iPhones and iPads etc.”

“Since Steve Jobs’ infamous speech about Flash, there has been a
decline in the use of Flash across the web. The number of jobs posted
has declined, the types of projects were focused mainly on games &
video players, interestingly, the budgets for Flash projects have risen due to the decline in the number of available Flash developer."

“Flash projects seemed to be everywhere in 2010, today you only see legacy projects that need minor updates to existing files and other misc support. There is no new development in flash at least in my area of expertise.”

“As far my observations, there were abundant jobs for flash in 2010 to 2012. After 2012 till 2015, flash jobs had been at a constant decline. But around 2016 till date, jobs related to Flash seems like increasing. I think because: 1. People want to port old flash apps to AS3, as flash still seems a suitable choice for executable or AIR for multiple platforms. 2. People also want to port old flash apps to HTML5.0 3. Flash games still seem to have a good hold in the market, and for various reasons preferred over HTML5.0 games. 4. There are some people who still want to carry on with their old flash apps, and ask for modifications and editing, or bug-fixing. 5. Adobe’s transformation from Flash to Animate CC, has added jobs for Create JS (however it’s not flash technically, but uses the same IDE)”

“Definitely a drop in available jobs/job postings. I have found the offer rate has gone up (maybe since the talent pool is smaller now).”

If you have noticed changes, what business, economic, or technological factors, do you feel, were the primary CAUSES of these changes in the market for Flash projects?

“Steve Jobs not letting Flash platform on Apple devices is the primary reason. It was not big issue, but the way flash was portait as evil, people could not understand the whole scenario. Secondary is Android ditching Flash. However, Adobe has found new way to get into those devices as in the form of Native Air apps. But one great vague thing for the users is, they are very confused with the term ‘Flash’. I have to make them clear about Flash Player, Adobe Flash (Animate), Adobe Air (Air player) and how Flash can be used in Mobile/Tablet platforms.”

“there was a campaign against flash for a long time and adobe really fumbled the ball, never defending it or improving it appropriately. steve jobs wrote a nasty little hit piece before he died and that really was a turning point. before that me and my partner were working for big clients, making good money, even working with Adobe itself. hahaha he ruined everything. thanks for nothing steve! (but it’s really adobes fault for failing to handle the situation at all)..”
How, if it all, does switching to a new technology affect the types of projects you select?

“Switching to new technology implies that you cannot directly go to expert level projects. It requires starting with easy level and enhance your learning as you work more on live projects.”

“When working with a new technology, I start with simpler projects compared to what I would normally work in using a technology I have already been using for a long time. As I get more projects in with the new tech, I start applying for more complex jobs.”

How, if it all, does switching to a new technology affect the amount you bid on these projects?

“Discounts for first few projects, after portfolio is built, like 2-3 successful projects, will bid full amount.”

“When switching to a new technology, I start with lower bids first, and then move on to high bids as I gain experience.”

“If I was switching to say some javascript I would bid low to build up experience and a portfolio in that technology but still be paid something while learning. pretty good deal to get paid anything at all if you’re learning a bunch while you go.”

5.5 Discussion of survey results

The tables above suggest that Flash developers experienced a significant decline in demand for their Flash skills, and that this affected the hours they spent on Flash projects more than it did the wages they earned. Part of the reason may have been that many developers fled Flash technologies, but others who focused heavily on Flash stayed with the technology and continued working on legacy and repair projects that required specialized knowledge at potentially higher wage rates.

The survey evidence provides qualitative support for our interpretation of the archival evidence. Workers were affected by changes in the market for Adobe Flash in some different ways. The survey evidence supports the argument that the elastic nature of the supply response that we observe in the archival data can be explained by the fact that workers acquire skills on-the-job, and therefore switch to new technologies more rapidly than might be suggested by a simple supply and demand framework.
6 Conclusions

The decline of Flash provides a stark example of how a technology can be displaced. Our main empirical finding is that despite a large reduction in demand, workers in Flash fared quite well. They proved, at least collectively, to be remarkably elastic, with discernable evidence of a decline in their wages. Of course, our results come from a particular context where technological shocks are commonplace and the pace of technological change is quick. Furthermore, there are many “nearby” skills that affected workers can re-orient themselves towards. Other skills might offer fewer adjustment options. However, the waxing and waning of the returns to highly specific human capital is commonplace in a dynamic economy.

Although our setting might tell us little about how relatively low-skilled displaced workers are likely to fare, how high-skilled, technology-focused workers adjust is of direct importance. Many new technologies have a complementary labor component, and the diffusion of that technology could, in principle, depend on how quickly complementary skills appear.

Workers do report being reluctant to adopt some new technology without evidence of its likely success. However, they do not appear to be stubborn about persisting with a “dying” technology—at least collectively, they are so elastic that we only observe a quantity effect, despite a massive reduction in demand. This is potentially important for the technology adoption—if hiring workers with a waning skill became dramatically cheaper, we might see less use of that technology than we otherwise would. Instead, if firms have a pay premium to use a legacy technology, the diffusion of new technologies will not be slowed down a cost disadvantage.

Our survey evidence does speak to why we might observe such a quick reaction. Respondents are clearly forward-looking about their human capital choices. And while they do report relying on their existing skills, they also learn new skills and deepen those that they have. They do this largely by on-the-job training, adopting a “learn while you earn” approach to adjustment. Interestingly, many report offering discounts to learn new skills, suggesting another reason why new diffusion might be accelerated, as using a new technology might attract eager students at relatively low prices.
References


